Three Essays in the Economics of Price Setting

by

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This thesis is dedicated to Sylvia Perry (née Rees), who fought World War II, moved to Canada, raised four children, and only then went into academia.

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ABSTRACT

This dissertation concerns the economics of price setting in both the industrial organization and macroeconomics literature. Across three chapters, I document salient features of prices and model their behavior. In the first chapter, we reconcile the potential for collusion in a product market, with frequent large sales, by building and estimating a model of collusion that allows producers to temporarily be on sale. In the second chapter, we document new facts about the frequency at the product level with which regular prices change, firstly that they are more likely to change the higher the revenue of the product, secondly that given they change they change by less the higher the revenue of the product. We embed these facts in a menu cost model, and show their importance to aggregate dynamics. Finally in my third chapter, we recover firm level markups using a model of final good inventories, that encompasses dynamic incentives.

In my first chapter, joint with DongIk Kang, we argue that temporary price reductions (or sales) are a result of a strategic interaction between potentially colluding firms. Rather than interpreting all price reductions as defections, sales are permitted in a tacitly collusive equilibrium, due to the presence of large negative shocks to marginal cost. Private information over the presence of the shocks imply an incentive

for the producers to mimic the low costs, in equilibrium producers will play a mixed strategy. We estimate the demand and cost primitives in the retail beer market that are consistent with our model. We find that sales are a relatively important part of the producers strategy, as under our model unilateral deviation to no-sales would reduce profit by 4-6%. Our equilibrium is also compared to an equilibrium where all firms charge only a regular price and never go on sale, we find that this no-sales equilibrium is less stable than the sales equilibrium in terms of minimum discount factor that could support it.

In my second chapter, also joint with DongIk Kang, we shift our attention to the menu cost literature. Revenue variation across products and time directly affects price setting decisions and monetary policy transmission. As product revenue rises, the probability of price adjustment increases while the absolute size of adjustment decreases. In addition, monetary policy shocks have heterogeneous effects on prices depending on product revenue: the responsiveness of prices increases with revenue. We verify these facts empirically, and show that they are consistent with predictions from a menu cost model in which the menu cost does not increase proportionally with revenue. We find that this heterogeneity in price responsiveness has important implications for monetary policy transmission using a calibrated menu cost model.

In my third chapter, joint with Alberto Arredondo Chavez, we use firm-level data on stocks of final goods and sales in order to estimate the change in firm-level markups through time. We extend a model of stock-out prevention to accommodate a variety of price-setting behavior. This allows us to be agnostic about the product market structure. Everything else equal, a higher markup implies a higher stock to sales ratio as the loss from a stock-out is larger. Three other components are key in order to identify markups with our model: the rate at which the firm discounts future flows, the expected growth in marginal costs and the strength of the need for inventories to prevent stock-outs. We use our information at the firm level to measure these components and recover markups.

CHAPTER I

Temporary Price Reductions and Competition: Evidence From The Retail Beer Market

1.1 Introduction

Discussion of the possibility of cooperation in pricing between producers dates to at least Adam Smith. With few competitors, an opportunity arises to raise prices to benefit each competitor. Such an arrangement is tempered, however, by the incentive to undercut each other. At the same time, producers experience constant changes in demand and cost conditions. One strategy producers use to take advantage of these changes is a temporary price reduction (or sale[1]). A naive observer would view these price cuts as evidence that the market was not collusive, however, in this paper we view the price reductions are a major part of the tacitly collusive strategy. Producers will not immediately punish each other for sales, instead we model sales as a part of

[1]Henceforth sales for the sake of brevity. When confusion might arise between revenue and the other common meaning of sales we will use revenue.

the collusive equilibrium. We take this idea to the retail beer industry and estimate the demand and cost primitives. We find each producer would have their profit reduced by approximately 1-8% by switching to a comparative no-sale equilibrium. In addition, we find that the sales equilibrium is more sustainable in terms of the minimum discount factor that could support it than the no-sale equilibrium.

Sales are a common phenomenon, according to the CPI micro data from the Bureau of Labor Statistics (Midrigan Kehoe 2015) 72% of all price changes are temporary, and 50% of all changes revert to their initial regular price. In addition, the average size of the discount offered is 11%. In another more narrow data-set 35% of all goods sold were sold on sale.[2] We take these facts as evidence that sales are a phenomenon worthy of more interest. Recent empirical research on collusion assumes that sales are either exogenous or unimportant to the equilibrium, this paper takes the opposite view and treats sales as a strategic variable.

Our main results show how temporary price reductions play an important role in sustaining collusion. The presence of large shocks to marginal cost give producers a strong incentive to undercut others by setting a lower price. In the equilibrium that allows sales, producers are allowed to take advantage of these periods. This has two effects on the ability for firms to sustain collusion, firstly this raises the profitability of remaining collusive relative to the punishment or single period equilibrium profit. Secondly, because the prices of the products on sale are closer to the one period optimal price, the payoff from defection decreases. The higher profit on the collusive path the more sustainable the collusive equilibrium, all else equal. Additionally, the

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[2]Midrigan and Kehoe (2015), using Dominick's Finer Foods 1989-1994.

lower the profit from defection the more sustainable the equilibrium, all else equal. We confirm this intuition by calculating the minimum discount factor required to sustain the equilibrium with sales we observe and a no-sale equilibrium where firms only charge the regular price in each market. Indeed over our sample we find that the minimum discount factor that could sustain the sales equilibrium is lower than the no-sales equilibrium.

We focus on the American retail beer industry for the following reasons: it is a well defined market with standardized products across markets. In addition, there are a few large producers Anheuser-Busch Inbev (main brands Budweiser and Bud Light), SABMiller (main brands Miller Genuine Draft and Miller Lite), and Molson Coors (main brands Coors and Coors Lite) that appear to dominate the market and have been suspected of tacit collusion. A recent treatment of this industry, Miller and Weinberg (2017) has illustrated the possibility of collusion intensifying after the merger between two of the three largest firms, Miller and Coors. We choose to focus on the temporary price reductions in this industry and their strategic content.

Our work extends three strands of literature, firstly the work on collusion modeled as the result of a super game. Papers such as Porter (1983) and Bresnahan (1987) began a literature that explicitly modeled market outcomes as a game between the participants in the market. Specifically we extend the empirical literature on dynamic competition. We build on work by Black Crawford Liu and White (2004) and Fan and Sullivan (2017), adding an additional stage of competition in each period that allows producers to respond to cost shocks. These models assume that all play is on equilibrium path, that is the firms never deviate from the collusive outcome during the sample. Instead changes in the competitive outcome come from changes in the primitives of the game, or the equilibrium that the firms are playing. Several industries have been examined for example: Sullivan (unpublished) models the choice of product mix in the premium ice cream market, Igami and Sugayaz (2018) study the vitamin market, and Miller and Weinberg (2017) in beer. These papers do not directly observe collusion or the primitives of the supply side and therefore must make substantive assumptions on the nature of the supply side.

Another literature works somewhat in reverse, starting from legal or regulatory information that collusion was more than tacit and seeks to examine its result. For example Clark Houde (2013) and Asker (2010) benefit from legal proceedings actually used to convict firms of illegal conduct. In more recent work, Eizenberg and Shilian (2019) study several supermarket categories, building a measure of the degree of collusion by looking for the minimum discount factor that would support the perfectly collusive outcome. Miller, Sheu and Weinberg (2019) model the retail beer market as having a clear market leader sets a price and the other producers decide to accept it, or defect from it. We offer a model that allows for intermediate amounts of collusion, that also treats the producers symmetrically.

We are also closely related to the literature that studies temporary price reductions. Chevalier, Kashyap, Rossi (2003) examine movement of prices in periods of high demand, and find that higher demand appear correlated with lower prices. There is also a great deal of discussion of temporary price reductions in the macroeconomics literature, Anderson Malin Nakuruma Simester and Stiensson (2017) present some institutional details about the nature of producer-retailer contracts that allow for sales. Particularly of interest to our paper, sales appear to come from a "sticky plan". Firms do not necessarily respond local demand and cost conditions, instead the producers set windows with in which the retailers are supposed to put the good on sale. This allows retailers limited flexibility. Another important paper for our context is Midrigan and Kehoe (2015), which in addition to showing that the non-sale or regular price is fairly sticky or slow to change. In addition, this paper introduced an algorithm that allows us to determine the regular price and sale price in the absence of direct recording of this in the data.

Thirdly, we add to the literature that uses mixed strategies to model real world outcomes. Papers such Azar and Bar Eli (2011) examine the context of soccer penalty kicks and find that in this high stakes but simple context that mixed strategy Nash Equilibrium rationalizes players choices better than competing models. Chiappori, Levitt, and Groseclose (2002) examined the same context and could not reject that players with heterogeneous skill levels were playing the mixed strategy Nash Equilibrium. In the Industrial Organization literature most authors restrict their analysis to games with pure strategy equilibria. Bajari Hong and Ryan (2010), in contrast, show in the context of entry games, that allowing for mixed strategies allows for the identification of the primitives of the payoff function.

The next section details the data we use and show descriptive evidence of the equilibrium outcomes in the beer market, then we introduce a model of sales behavior, following that we estimate the model. Finally, we show our equilibrium is more profitable and more sustainable than a no-sale equilibrium that does not allow temporary price reductions over the sample.

1.2 Data and descriptive evidence

The primary data this paper uses is the Nielsen Retailer Scanner database obtained through the Kilts Marketing Center at the University of Chicago Booth. We use the data from 32 of the designated market areas (DMAs), these are listed in Appendix A. We use data from 2007 to 2015, we aggregate weekly data to monthly to alleviate concerns about measurement error. In addition, this aggregation alleviates concerns that demand may have dynamic considerations, driven by storage by the consumers. We deflate the prices by the Food and Beverage CPI deflator for all Urban Consumers.

In the data not all of the sale prices are flagged, therefore we make use the algorithm introduced by Midrigan and Kehoe (2014) to compute regular prices. In other work, we used the same procedure on the Nielsen scanner data but with a larger set of products. The algorithm determines the regular price as the modal price in an 11-week window surrounding each week provided the modal price is used sufficiently often.[3] If the modal price is not used more than two-thirds of the time in a given 11 week window than the current price is determined to be the regular price. We use this as our measure of whether a given good is on sale in a given week in a given store.

We differ from some of the existing literature in industrial organization by using such an algorithm. Papers such as Hendel Nevo (2006) have used different definitions of regular price, such as the maximum or mode in a certain period. We believe the

[3]A detailed description of the algorithm we use to compute regular prices can be found in the appendix of Midrigan Kehoe (2013).

algorithm from Midrigan Kehoe (2014) is more likely to pick up sales rather than staggered price increases. Additionally the literature varies on the depth of sale to classify a price as a sale or not. Hendel and Nevo (2006) consider various depths of sale (1%, 10%, 25%, 50%). We find that the large depths of sale are very infrequent in our sample, for this reason we use 3%.

Table 1.1 includes the summary statstics of the sample we use for demand estimation. We convert all prices into 12 packs of 12 oz equivalents, by dividing by the number of onces in the product and multiplying by 144.

Table 1.1: Summary Statistics: Demand Estimation Sample

	Monthly Rev.	Average Price	Regular Price	Sale Price	% on Sale
Mean	53966	10.99	11.10	10.23	12.55
Median	14744	10.70	10.77	9.73	3.12
Std. Dev.	107568	2.71	2.72	2.55	17.90
N	170,773				

Notes: Prices from Nielsen. Regular price calculated using algorthim from Midrigan Kehoe (2014). Deflated by Personal Consumption Expenditure: Deflator Food and Beverages. All prices converted to 12 pack of 12 oz servings equivalent.

For the current supply specification we estimate the costs for only the 12 packs for the three largest producers (Coors, Miller and Budweiser). In table 1.2 we present summary statstics of the sample we use for the current supply estimation. The products in this sample are slightly cheaper and slightly less likely to go on sale than the entire sample. We plan to extend our supply estimation sample to encompass a larger portion of the data.

Table 1.2: Summary Statistics: Supply Estimation Sample

	Monthly Rev	Average Price	Regular Price	Sale Price	% on Sale
Mean	71501	9.95	10.04	9.46	10.99
Median	29397	10.04	10.13	9.53	6.52
Std. Dev.	100015	1.03	1.04	1.09	12.91
N	20,630				

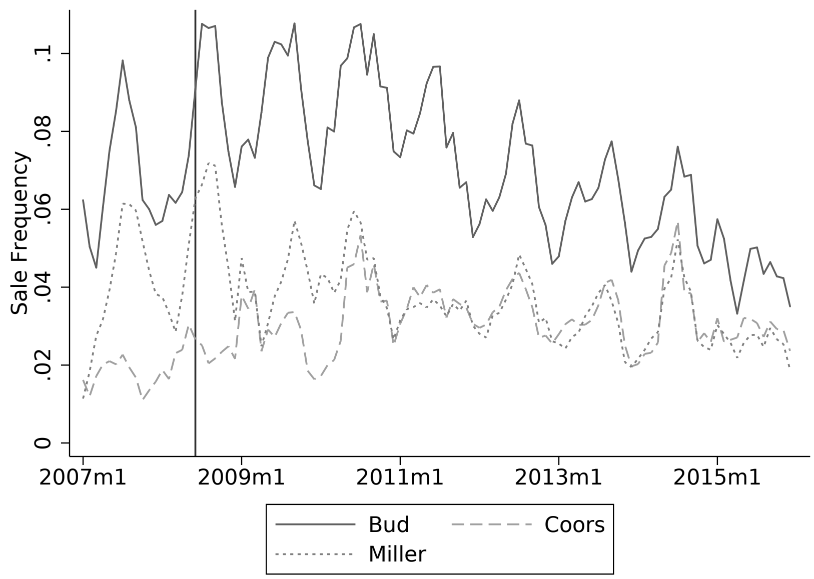
Notes: Prices from Nielsen. Regular price calculated using algorthim from Midrigan Kehoe (2014). All prices converted to 12 pack of 12 oz servings equivalent. Includes only the 12 packs of the leading regular and light beers for Miller Coors and Budwieser.

1.2.1 Reduced form evidence

In this section we look for descriptive evidence suggesting sales matter for understanding competition, and document the behavior of prices and sales throughout our sample. Mergers impact the degree of competition in a market, both in standard models and as empirically demonstrated by the literature. Since we believe that the frequency of sales is a strategic variable we investigate the effect of a large merger on the frequency of sales. In addition, we document the impact of the merger on the other components of pricing, the regular price and the sale price.

In Figure 1.1 we show the median frequency of sales across markets and months. The frequency of sales for each market product was calculated by computing the fraction of quantity sold on sale in each market for each product. We find that the frequency of sales is fairly volatile, so we present a three month moving average of the median frequency across stores and products. Sales appear to be more frequent immediately after the merger for Budweiser and Miller, and increase later for Coors. From the beginning of 2012 on-wards there is a downward trend in the frequency of

Figure 1.1: Median frequency of sales



Note: Three month moving average of the median frequency of sales computed across markets and products. Sales computed using the algorithm from Midrigan Kehoe (2014). Sales were aggregated to the product market level by computing the fraction of quantity sold on sale in each market for each product. The red-line highlights the consummation of the merger between Miller and Coors.

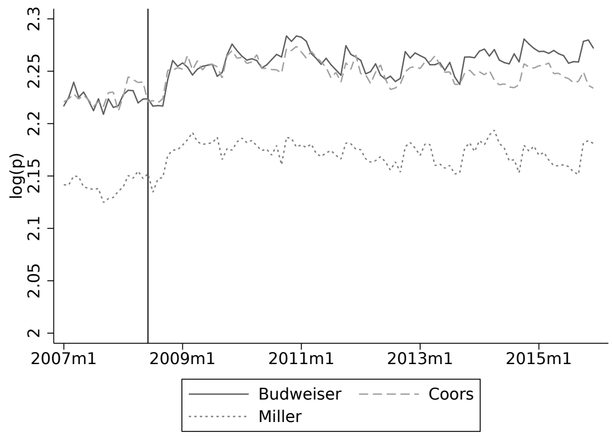
sales for all of the producers.

In Figure 1.2 we report the median prices across markets and goods for the three largest producers through time. We see a sizable impact of the merger between Miller and Coors on each of the levels of the prices. We see this across the average, regular and sales prices. Noticeably prices rose for Budweiser, while Budweiser was not one of the merging firms. This cannot be directly interpreted as evidence of collusion because of the direct effect of a removal of a competitor. Next, we summarize the effects of the merger on the main strategic variables in regression form.

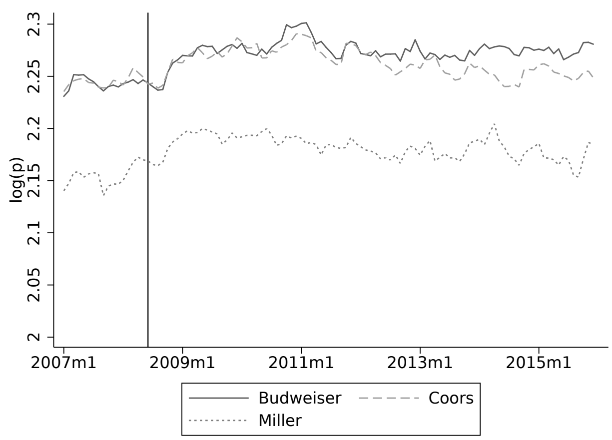
We show descriptive regression results to summarize the impact of the merger on the main strategic variables. We run these regressions at the product-market-month level, SALE_{jmt} is the frequency of sales, MC_j is a dummy variable for the product being sold by Miller-Coors, BUD_j is a dummy variable for the product being sold by Anheuser-Busch Inbev, and post_t is a dummy variable for the month being after the merger was consummated. The inclusion of Michelob, Heineken and Corona are to form a control group of firms that neither merge nor are conjectured to be part of a pricing coalition. They are not controlled by any of the three major breweries but are large national brands. We exclude the period June 2008 to April 2009 to account for immediate complications leading up to and after the merger. For these regressions we limit the sample to January 2007 to December 2012 to focus on the effects of the merger on the strategic variables in the aftermath. We use the following specification reported in Table 1.3:

Figure 1.2: Median Real Prices

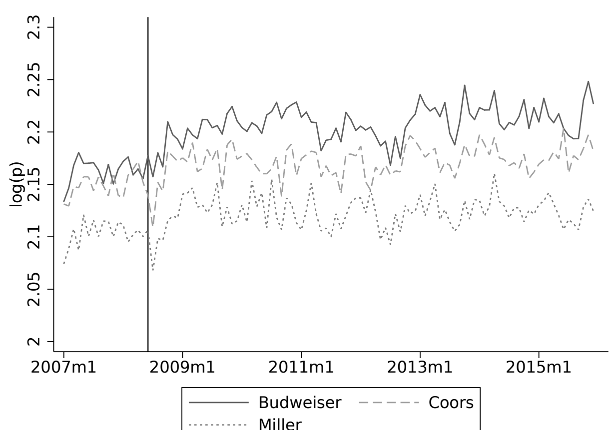
(a) Average Price



(b) Regular Price



(c) Sale Price



Note: Median real prices per 144 oz. Across 32 markets. Prices deflated by the Personal Consumption Expenditure: Food and Beverage Deflator. Sales computed using the algorithm from Midrigan Kehoe (2014). The red-line highlights the consummation of the merger between Miller and Coors.

$$
\begin{aligned}
\mathrm{SALE}_{jmt} =& \beta_{MC} * \mathrm{MC}_j + \beta_{BUD} * \mathrm{BUD}_j + \beta_{merge} * \mathrm{post}_t \\
&+ \beta_{MC*merge} * \mathrm{MC}_j * \mathrm{post}_t \\
&+ \beta_{BUD*merge} * \mathrm{BUD}_j * \mathrm{post}_t + \epsilon_{jmt}
\end{aligned}
$$

Across specifications it is apparent sales increased for not only the merging firms but for Budweiser as well. The effect becomes larger with the inclusion of brand specific specific trends suggesting that while the frequency of sales was falling overall in this market, the merger had a positive effect. Our model presented in Section 1.3 does not imply a monotonic relationship between the frequency of sales and the degree of collusion. We interpret these results therefore as suggestive of the importance of changes in competition on the strategic variable that we study, namely the frequency of price reductions.

We also estimate the effect of the merger on the prices. We run separate regressions on average prices, regular prices, and sale prices. We run a similar difference in difference as Miller and Weinberg (2017):

$$
\begin{aligned}
\log(\mathrm{P})_{jmt} =& \beta_{MC} * \mathrm{MC}_j + \beta_{BUD} * \mathrm{BUD}_j + \beta_{merge} * \mathrm{post}_t \\
&+ \beta_{MC*post} * \mathrm{MC}_j * \mathrm{post}_t \\
&+ \beta_{BUD*post} * \mathrm{BUD}_j * \mathrm{post}_t + \epsilon_{jmt}
\end{aligned}
$$

Table 1.3: Frequency of sales

	Percent on sale	Percent on sale	Percent on sale
post	-0.019		
	(0.004)		
post*bud	0.013	0.013	0.037
	(0.002)	(0.002)	(0.006)
post*miller-Coors	0.019	0.019	0.022
	(0.003)	(0.003)	(0.007)
Brand FEs	y	y	y
Time FEs	n	y	n
Brand Trends	n	n	y
Observations	109,523	109,523	109,523
R-squared	0.006	0.011	0.293

Note: Sales calculated using algorithm from Midrigan Kehoe (2014). The before sample includes Jan 2007 to June 2008 and April 2009 to December 2012. We include 6 12 24 and 30 packs of the major brands described in the text. The control group includes Michelob, Corona and Stella Artios.

Where the left hand side variable $\log(P)_{jmt}$ is the deflated average, regular, or sale price per 144 oz of beer in logarithms. The first column in these tables are without fixed effects, the second column has date and brand fixed effects, while the last column has brand fixed effects as well as brand specific trends. All standard errors here are clustered on date. We model the effect at the market brand-size month level. We exclude the period May 2008 to April 2009 to account for immediate complications leading up to and after the merger. For these regressions we limit the sample to Jan 2007 to December 2011 to focus on the effects of the merger.

These tables show that all prices sharply rose after the merger, for the firms that merged as well as for Budweiser relative to the other brands. The coefficients appear slightly smaller with the inclusion of the brand-specific trends which suggest that the

Table 1.4: Effect of Miller Coors merger on Prices

(a) Average Price

	$\log(\bar{P})$	$\log(\bar{P})$	$\log(\bar{P})$
post	-0.0445		
	(0.00348)		
post*Budwieser	0.0841	0.0825	0.0410
	(0.00370)	(0.00374)	(0.00419)
post* Miller+Coors	0.0847	0.0826	0.0330
	(0.00381)	(0.00388)	(0.00485)
Observations	109,532	109,532	109,532
R-squared	0.542	0.560	0.995

(b) Regular Price

	$\log(P^R)$	$\log(P^R)$	$\log(P^R)$
post	-0.0466		
	(0.00346)		
post*Budwieser	0.0860	0.0846	0.0464
	(0.00345)	(0.00349)	(0.00364)
post*Miller+Coors	0.0865	0.0845	0.0372
	(0.00365)	(0.00371)	(0.00452)
Observations	109,532	109,532	109,532
R-squared	0.555	0.573	0.995

(c) Sale Price

	$\log(P^S)$	$\log(P^S)$	$\log(P^S)$
post	-0.0526		
	(0.00361)		
post*Budwieser	0.0953	0.0948	0.0355
	(0.00319)	(0.00321)	(0.00490)
post*Miller+Coors	0.0826	0.0821	0.0161
	(0.00397)	(0.00402)	(0.00674)
Observations	72,003	72,003	72,003
R-squared	0.584	0.592	0.995
Brand FEs	y	y	y
Time FEs	n	y	n
Brand Trends	n	n	y

Note: Sales calculated using algorithm from Midrigan Kehoe (2014). The before sample includes Jan 2007 to June 2008 and April 2009 to December 2012. We include 6 12 24 and 30 packs of the major brands described in the text. The control group includes Michelob, Corona and Stella Artios. Standard Errors computed using monthly clusters.

brands may have prices that trended differently for reasons other than the merger. This section has shown descriptive evidence of the effects of the merger between Miller and Coors. While this merger is not the major focus of this paper, it allows some inference into the effects of a major shift in competitive environment, as well as important background for the market.

1.3 Model of sales in a collusive equilibrium

In this section we develop a model of price setting that allows for tacit collusion. We model the producers as setting two prices per market, to fit the reality of regular prices and lower sales prices. We use this model to give a rationalization for producer behavior, then to estimate the cost primitives of the producers, and finally in section 1.5 we use the model and the estimated primitives to compare the proposed equilibrium which allows sales to one that does not. To fix ideas we present the stage game in a very simplified form, only one market and two competitors with one good each. After this we will show how the game changes as we generalize to many competitors and many product producers. Finally, we discuss this stage game in the context of a dynamic game where the producers will play this game repeatedly, but with primitives that are allowed to change through time.

1.3.1 Setting

We consider a small number of producers (Budweiser, Miller, Coors) that produce beer. We assume they contract with retailers across several markets. The retailers are given little latitude in pricing, they can choose which price to offer between the sale and regular price that the producer sets, with the total frequency of sale determined by the producer. They do however, internalize the impact that those prices have on the profits of the producer (the contracting problem between the retailer and the producer is solved to maximize the profits of the producer.) In each market we assume there is a continuum of identical retailers, and a continuum heterogeneous of consumers at each store. We interpret the results of Anderson Malin Nakuruma Simester and Stiensson (2017) to mean that some freedom is granted to the retailer to pick the timing of the sales, but not complete freedom over pricing.

There are several reasons that producers might have an incentive to go on sale, we assume that the major driver of sales are temporary but large negative shocks to marginal cost. Other reasons include: a transitory idiosyncratic demand shock, a transitory but common demand shock, and purely out of inter-temporal or general price discrimination. We believe the cost shock is the most natural in this context for the following reasons. Firstly, a transitory product-level demand shock would cause producers to temporarily raise their prices, contrary to the observation of price reductions. We also do not believe that the transitory product demand component is that important in the beer market. Next, we believe that there are common demand shocks in the beer market, however these are likely driven by forecast-able events–such as sporting events, holidays, or seasons–are not private information, we choose not to focus on these. Temporary sales could arise out of the desire to take advantage of inter-temporal price discrimination. However, we believe that beer is less likely to be stored between weeks or months than other goods traditionally considered, such as laundry detergent. We also take the view that price discrimination without a underlying shock is unlikely as a source of temporary price reductions, we believe that the presence of cost shocks is a primitive that producers can coordinate over. It is possible in theory for sales to be rationalized without transitory shocks; however, we believe that cost shocks are the most natural source.

For each product the producer receives an idiosyncratic shock to its cost, we interpret this as reflecting a negative shock to the cost of the good. This shock is private information to the other producers, therefore the other producers consider the realization of the shock as a random variable when setting their prices. One way this shock could be interpreted as unexpected excess inventory, where the cost reflects not the cost of production but the opportunity cost of the storage and carrying cost. These costs could even become negative, justified by a lack of free disposal. In each period of play producers first choose a regular price for each product in each market, then they choose a sale price for those goods that receive the large cost shock, and for each good that does not decides whether to mimic the sale price or stay at the regular price.

We assume that there is a continuum of identical stores in each market and that the shocks to marginal cost are independent across stores. This implies that the incentive constraint from the producer's perspective depends shares equal to the probability of the shock, or the probability of the price that other producers will charge. We assume at each store there is a continuum of heterogeneous consumers, where the distribution is identical across retailer in the same market. We do not consider strategic behavior on part of the consumers, other than for producers to face an identical static demand system at each retailer.

1.3.2 Simple Stage-Game Model

We begin with the two producer case where each producer has a single product to fix ideas, and then we generalize to the multi-product producer multi-producer model we estimate.

Consider a two stage game where producers choose the regular price in the first stage and in the second stage decide whether or not to put their product on sale. After firms choose the regular price is stage 1, the cost of each producer $c_j \in \{c_j^N, c_j^S\}$ is revealed to the producer at which point the producer can decide to go on sale or not. The product's marginal price will either be normal c_j^N with probability $1 - r_j$ or low c_j^S with probability r_j. While the distribution of each firms costs is public information, the realizations are private. Firms learn their own costs, and then determine the sale price, and whether to go on sale. Then the firms can choose to lower their prices so as to defect from the dynamic equilibrium, defection can only take place for products not on sale. This assumption is equivalent to assuming producers can only change their price once in the second period.

The equilibrium strategy that we consider is as follows: in stage 1, producers choose a collusive regular price p_j^R that yields a higher profit then the Bertrand Nash equilibrium, unless in the history of play any producers did not choose this price, at which point all firms will play the Bertrand Nash forever. If any producers chooses any other price at this stage, all producers play the Nash Bertrand equilibrium strategy in the second stage, this means no firm will deviate in this stage.

In stage 2, retailers that have cost c_j^S will choose the optimal price p_j^S for that product in the current period only. This a substantive assumption on the equilibrium, effectively the other producers are giving the producer a chance to take full advantage of the shock. If retailers have cost c_j^N they will mix between playing their regular price with probability $1 - m_j$ and sale price with probability m_j. Then producers could deviate in all retailers simultaneously. Finally, producers realize profits and learn the other firm's prices. [4]

Solution to stage 2:

Take $p^R = (p_1^R, p_2^R)$ as given. Note that under the equilibrium strategy, the other firm's price p_2 will be:

$$p_2 = \left\{ \begin{array}{ccccc} p_2^R & : & (1-r_2)(1-m_2) & \Rightarrow & (1-\alpha_2) \\ p_2^S & : & r_2 + (1-r_2)m_2 & \Rightarrow & \alpha_2 \end{array} \right\}$$

Following the equilibrium strategy, p_1^S is the optimal price for firm 1 in a single period. Then p_1^S solves:

$$\max_{p_1} \quad (1-\alpha)(p_1 - c_1^S)q_1(p_1, p_2^R) + \alpha(p_1 - c_1^S)q_1(p_1, p_2^S)$$

Then given α_2, p_2^R, p_2^S, we can solve for p_1^S.[5] The same is true for p_2^S. Therefore the sale price can be written: $p_i^S(p^R, \alpha_1, \alpha_2)$.

When retailers do not receive the shock: $c_1 = c_1^S$, in the equilibrium strategy they will play a mixed strategy. To do so, player 1 will be indifferent between playing p_1^R

[4]Bernheim and Whinston (1990) argue that if you are going to be punished, you might as well deviate in all markets and all products.

[5]We assume that the demand system is sufficiently smooth and well behaved to allow this.

and p_1^S. Therefore:

$$\pi_1^N(p_1^R, p_2) = (p_1^R - c_1^N)\Big\{(1-\alpha_2)q_1(p_1^R, p_2^R) + \alpha_2 q_1(p_1^R, p_2^S)\Big\}$$
$$\pi_1^N(p_1^S, p_2) = (p_1^S - c_1^N)\Big\{(1-\alpha_2)q_1(p_1^S, p_2^R) + \alpha_2 q_1(p_1^S, p_2^S)\Big\}$$

Additionally for mixed-strategy to be an equilibrium strategy, producer 2 must choose α_2 such that $\pi_1^N(p_1^R) = \pi_1^N(p_1^S)$. Same for producer 1 and α_1.

Incentive Constraints:

When $c_i = c_i^S$ retailers are unable to change the price of that product.[6] When $c_i = c_i^N$, because playing mixed-strategy implies producers are indifferent between playing p_i^R and p_i^S, producers have no incentive to deviate from one to the other. Producers do have the incentive to deviate to a price other than p_i^R and p_i^S. The equilibrium strategy punishment scheme to stop this behavior is a return to the Nash-Bertrand equilibrium. This constraint must be considered by the producers choosing the regular price in stage 1. The constraint for the producer 1 is:

$$\begin{aligned}&\mathbb{E}_{p_2}\big[\alpha_1\pi_1^N(p_1^R, p_2) + r_1\pi_1^S(p_1^S, p_2) + (1-r_1)m_1\pi_1^N(p_1^S, p_2)\big]\\ \geq\ &\mathbb{E}_{p_2}\big[\alpha_1\pi_1^N(p_1^D, p_2) + r_1\pi_1^S(p_1^S, p_2) + (1-r_1)m_1\pi_1^N(p_1^S, p_2)\big]\end{aligned}$$

[6]Additionally, in the single product market producers would not want to change the price from the sale price as that solves the single period profit maximization problem.

Simplifying: $\mathbb{E}_{p_2}[\pi_1^N(p_1^R, p_2)] \geq \mathbb{E}_{p_2}[\alpha_1 \pi_1^N(p_1^D, p_2)]$. Producers will take into account the constraint and how it changes when choosing p_i^R. We have shown that our conjectured equilibrium indeed is an equilibrium of the stage game, and now will discuss the more general model.

1.3.3 Multi-producer Multi-product stage game

In this section we extend the model from the previous section to encompasses more realistic cases, multiple markets, multiple producers, and multi product producers.

First we introduce subscripts for the notation. There will be a continuum of consumers i in each market m at each time period (month) t. There are producers f, that sell products $j \in F_j$ in stores s. We assume that consumers visit one store from the continuum of stores, which are ex ante identical, consumers only learn the prices the store charges upon arrival and cannot switch stores.

We assume that all the costs (c_{jmt}^S, c_{jmt}^N and r_{jmt}) as well as the demand unobservables (δ_{jmt}) follow exogenous first order Markov processes. This allows us to separate the periods of the game, the only endogenous state variable is previous play of the game. We name these states Θ_t.

Timing of the model within each period:

1. First, mc_{jmt}^S the level of the shocked marginal cost of good j, mc_{jmt}^N the level of the unshocked marginal cost of good j , and δ_{jmt} the mean utilities of each good are revealed. In addition, the frequency of the marginal cost shocks r_{jmt} is revealed. These are all public information.

2. Second, each producer give all retailers the same instructions for each good

in a market. The retailers will choose between P^s_{jmt} the sale price, and P^R_{jmt} the no sale or regular price. Retailers will be allowed to sell at the sale price α_{jmt} of the time, (this contains the same information as is given by stating the mixed strategy μ_{jmt} as r_{jmt} is known to all parties.) Defection at this stage is possible, however as it can be immediately punished in the current period t no producer will defect here.

3. Retailers realize the cost shock, this is private information to the other producers. The retailer will choose P^s_{jmt} with certainty if it has received the shock. If it has not it will play p^S_{jmt} with probability m_{jmt} and P^R_{jmt} with probability $(1 - m_{jmt})$. Stores make the pricing decision and the decision whether to go on sale without knowledge of the shock for other goods, or indeed the shocks and prices at other stores.

4. Finally, the producers decide whether to send the signal to defect, only unshocked goods at stores will sell products at the single shot deviation profit maximizing price. Other producers cannot respond until the next period. As there is a continuum of stores, the producers will treat the decision to defect as if the profit were the expectation.

We previously proved an equilibrium exists for the two producer single product producer case, here is a sketch of the proof for the more general world: as the regular prices are chosen to maximize profits given the incentive compatibility constraint is satisfied the producers do not wish to deviate to a different regular price. After resolution of uncertainty the shocked products will be sold at a price that solves the static profit maximization problem. The unshocked products will have prices that are some times the sale price and at others the regular price, because this results from a mixed strategy the producer will be indifferent between choosing the sale or regular price. Therefore the producer will have incentive to deviate to either price. Defecting producers would defect in every product that has not been put on sale.

1.3.4 Dynamic Game: Pareto Refinement

Producers play a dynamic game where each period evolves as above. We assume that there are no endogenous state variables beyond a binary variable that contains whether any producer has defected in the past. This ensures that prices chosen today have no impact future choices except where the cause punishment. We assume that the dynamic game has symmetric grim trigger strategies in equilibrium. That is the producers will play a specific collusive regular price outlined below, a sale price consistent with single shot profit maximization given they have received the shock, and a frequency of sale that is consistent with the mixed strategy in each market. If any producer fails to play this strategy all producers will interpret that as defection and will price at the single shot Nash Bertrand Equilibrium for all periods after the current one.[7]

In order to make progress towards estimation we take a further refinement that we believe is natural. We assume producers act as if profit were maximized by a planner with Pareto weights ω_f. Black Crawford Liu and White (2005) introduced

[7]If any producer were to defect before the end of a certain stage, they could be punished immediately therefore the only deviation we have to consider is at the end of the period.

this refinement in the context of a price setting game terming it “Virtual Stakes”. More recently Fan and Sullivan (2019) have examined the assumption in more detail. The assumption of Pareto optimalitity ensures that no producer could earn a higher profit without another producer suffering. Per period welfare is:

$$\mathbb{P}(p_t^R; \Theta_t) = \sum_f \omega_f \sum_m \mathbb{E}\pi_{fmt}(p_{jmt}^R)$$

The objective function that the Pareto planner optimizes is $\sum_{\tau=0}^{\infty} \delta^\tau \mathbb{E}_{\Theta_{t+\tau}|\Theta_t} \mathbb{P}(p_{t+\tau}^R; \Theta_{t+\tau})$ However, since we have assumed that all the components of Θ_t follows exogenous first order Markov, and we only ever observe producers playing the collusive part of the strategy, the choice of regular price only depends on the current profits.

$$\mathbb{E}\pi_{fmt}(p_{fmt}^R) = \sum_{j\in F} \sum_s (r_{mtj} f(s) \pi_{jmt}^S(p_{jmt}^R, p_{-jmt}(s)) + (1 - r_{jmt}) \pi_{jmt}^N(p^R, p_{-jmt}(s)))$$

is expected profit from the perspective of the first sub-period (before learning the realization of the marginal cost shock), $p_{-j}(s)$ represents the vector of all other prices and s the state of the other shocks. The expected profit from good j when the retailer does not receive the shock is $\pi_{jmt}^N(p_{jmt}^R) = \sum_s f(s)(1 - m_{jmt}) * (p_{jmt}^R - c_{jmt}^N) q_{jmt}(p_{jmt}^R, p_{-jmt}) + m_{jmt} * (p_{jmt}^S - c_{jmt}^N) q_{jmt}(p_{jmt}^R, p_{-jmt}))$ (m_{jmt} is the probability of going on sale when the product do not receive the shock, when products are going on sale from the mixed strategy). The profit from good j when the retailer does receive the shock is $\pi_{jmt}^N(p^R) = \sum_s f(s)(p_{jmt}^S - c_{jmt}^S) q_{jmt}(p_{jmt}^S, p_{-jmt})$.

There are a series of constraints to ensure this remains an equilibrium on path.

Each producer is ensured to not deviate from the equilibrium path. For each f at time t:

$$\sum_{t=1}^{\infty} \delta^t \Big[\mathbb{E}\pi_{ft}(p^R) - \mathbb{E}\pi_{ft}(p^B) \Big] \geq \mathbb{E}\pi_{f0}(p^D, p^R_{-f}) - \pi_{f0}(p^R)$$

Where P^D is the single shot profit maximizing deviation price for all products the producer owns, p^R_{-f} is the on equilibrium path prices for all goods the producer does not own, and P^B is the price vector coming from the punishment phase and any return to the equilibrium path. We have no data on defection or punishment, as we have assumed the producers have always been on the equilibrium path for our sample. For this reason we assume that the punishment is grim trigger, that is play the single shot Nash Equilibrium for all periods into the future. The constraint is that each producer must not wish to deviate from it's regular price after the revelation of the levels of its marginal costs. This framework was introduced by Black Crawford Lui and White (2005). Other papers such as Fan and Sullivan (2019), and Bernheim and Whinston (1990) have used the same constraints on equilibrium.

Therefore the tacitly collusive arrangement's problem can be rewritten as a series of Lagrangians. One producer f:

$$\max_{p^R} \quad \sum_f \omega_f \mathbb{E}\pi_f(p^R)$$

$$+ \sum_f \lambda_f \Big[\sum_{t=1}^{\infty} \delta^t \Big[\mathbb{E}\pi_{ft}(p^R) - \mathbb{E}\pi_{ft}(p^B) \Big] - \Big(\mathbb{E}\pi_{f0}(p^D, p^R_{-f}) - \pi_{f0}(p^R) \Big) \Big]$$

First order conditions ∂p_j^R for each j:

$$\omega_f \frac{\partial \mathbb{E}\pi_f(P^R)}{\partial p_{jmt}^R} + \sum_{f' \neq f} \omega_{f'} \frac{\partial \mathbb{E}\pi_f(P^R)}{\partial p_{jmt}^R} + \lambda_f \frac{\partial \mathbb{E}\pi_f^D(P_{jmt}^R, P_{-jmt}^R)}{\partial p_{jmt}^R}$$
$$- \sum_{f' \neq f} \lambda_{f'} \left(\frac{\partial \mathbb{E}\pi_{f'}^D(P_{f'}^D, P_{-f'}^R)}{\partial p_j^R} - \frac{\partial \mathbb{E}\pi_{f'}(P^R)}{\partial p_j^R} \right) = 0$$

Producers operate as if they were maximizing the joint profits with these constraints and weights. Intuitively producers care about the impact of their action (i) Their own profit, (ii) The profit of the other producer, (iii) the incentives to deviate in the second sub period. Notice the owner of j does not consider how changing p_j will impact the deviation price as that assumed that p_j for all $j \in F$ is chosen to maximize single period profit. The producer knows that it will be able to pick its deviation prices in the future. $\pi_f^D(P^R)$, the defection profit differs slightly from $\mathbb{E}\pi_f(P^R)$ in that the deviations are only made for goods that are not on sale, those on sale have their prices locked in.

On the equilibrium path regular prices and the sale prices will be accepted by the other members of the tacitly collusive arrangement, they will not be punished. However, all other prices will be considered cheating and be punished by Nash reversion. We assume that producers have a window to defect only after all other prices are set. Defections could happen at earlier stages, however those could be detected and punished, as every producer can defect at the last stage.

In contrast to traditional models of collusion, decreases in price to take advantage of a cost shock will not be punished. In addition the other producers will not know whether any individual retailer has received the shock for that good, this gives producers the incentive to allow retailers to mimic the state where they were shocked, by going on sale occasionally when they did not receive the shock.

We now turn to estimation of the primitives of this model.

1.4 Estimation

1.4.1 Demand

We estimate a random coefficient nested logit demand system. This allows for flexible estimation of cross price elasticity, papers such as Miller Weinberg (2017) and De Loecker Scott (2016) use similar models for the beer industry. We have credible exogenous variation due transportation costs, we can use the national cost of fuel interacted with the distance from the brewery (or port of import) to the market. We observe weekly transactions at every store in the Nielsen data, however we aggregate to the market month level for our structural analysis in part to alleviate concerns about storage, as well as to reduce measurement error. Prices are averaged across stores weighted by the volume of sales (we use observed transaction prices here neither sale or regular directly). We follow Miller Weinberg (2017) by building the distribution of preferences as functions of the income of household. We sample one hundred household per market from the American Community Survey. We use their income to build the distribution of prefernces allowing the constant as well as the coefficients for light beer, and for price to depend on the income of the households.

Utility of the customer j in market m for good i at time t is:

$$
\begin{aligned}
u_{ijmt} = &\alpha_{0income} * income_{jt} \\
&+ (\alpha_{price} + \alpha_{price,income} * income_{jt}) * (price_{imt}) \\
&+ (\alpha_{light,income} * income_{jt}) * (light_i) \\
&+ \tau_t + \tau_i + \tau_m \\
&+ \zeta_{jt} + (1-\rho) * \epsilon_{ijt}
\end{aligned}
$$

Where ζ_{jt} is distributed so ϵ_{ijt} is iid extreme value. ρ is the nesting coefficient on the inside option on the consumption of any beer in our sample. τ_t, τ_i, τ_m are time, product and market fixed effects respectively.

We use as non-linear instruments: mean income interacted with constant, prices, and light, as is suggested by Gandhi Houde (2016). We use the number of products as an instrument for the nesting parameter. To estimate the coefficients of the demand system in this paper, we use the posted price averaged over the stores in each market in each period weighting by total sales. We use only the best selling brands, that is Miller, Coors, Budweiser, Michelob, Stella Artios and Heineken in the 6-pack, 12-pack, 18-pack, 24-pack and 30-pack of their leading brand and its light counterpart.[8]

Table 1.5 reports the non-linear coefficients for the estimated demand system.

[8]All the data come from the 5000 Beer, and the 5001 Light Beer categories in the Nielsen Retail Scanner data.

Table 1.5: Demand Estimates

	Parameter	Std. Err.
$\alpha_{0income}$	0.001	0.245
$\alpha_{price,income}$	0.044	0.013
$\alpha_{light,income}$	0.001	0.089
α_{price}	-0.121	0.003
ρ	0.780	0.012
Mean Elasticity	-4.721	
n	170,773	

Note: Standard Errors clustered by month. Data market-product-monthly from Jan 2007 to Dec 2015, across 32 markets. Instruments include mean income interacted with constant price and light dummy, as well as fuel cost and the number of products.

They suggest that as household's income increases the demand for beer increases, as well as their preference for light beer while these relationship are fairly weak. The interaction between income and the price coefficient is also positive which suggests that as consumers have higher income their price sensitivity decreases. The mean elasticity appears to be within range of the relevant literature.

1.4.2 Supply

For the supply side estimation we face several conceptual issues. Firstly, for each store we only observe a sale price and a regular price when the good is on sale, otherwise we only observe the regular price. Secondly, some stores charge a permanently higher price than other stores, and discount from that price when on sale. To solve these issues we construct the average depth of sales in all stores in the market in a given period. We also calculate the average regular price across all stores in the market, from this we generate an sale price for the market time period by taking the average depth below the regular price. We construct the frequency of sales by taking the average of number of sale weeks weighted by the quantity of sales in each store divided by the number of weeks in each month. This gives us a continuous measure of the frequency of sales in each market.

In order to reduce the complexity of computation we focus on only 2 products per firm for the supply estimation, the flag ship beer and the light version[9] these account for the 20% of the total revenue of the total sample. We do this as the number of states grows exponentially in the number of goods in each market (2^J because each good can either be on sale or not). To generate a sale price and regular price at the market level, we construct an representative regular price by averaging the regular price charged at every store weighted by the volume of sales. We construct the sale price by averaging the depth of the sale in percent across stores that are on sale. This is to alleviate the problem of heterogeneity in which stores go on sale, if the higher price stores on average were to go on sale the average sale price might be higher than the regular price. We compute the frequency of sale by taking the simple average across stores of whether that store had a sale on that good. We assume that each product receives a shocked marginal cost independently across all stores. Additionally, we assume that the shock is independent across goods with in the same market or store.

We aggregate profit by summing across markets and products in a time t, the dervivatives are calculated at the market level are added weighted by market size. We recall some of the assumptions from Section 1.3 that allow us to solve the model.

[9](Budweiser, Bud Light, Miller High Life, Miller Light, Coors Light and Coors.)

Firstly, we assume that the P_j^S solves a single period maximization. Producers allow retailers to charge a price that comes from this first order condition. This is effectively a free pass from the other producers to charge the best price given a retailer has received the shock. Notice the choice is for only the products that have received the shock. That is:

$$P_j^S = \arg\max_p \sum_{s|jshocked} \{f(s|jshocked)(p - mc_j^S) * q_j(p, p_{-j}(s))$$

$$+ \sum_{j' \in F, j' \neq j} (p_{j'}(s) - mc_{j'}(s)) * q_j'(p, P_{-j}(s)\}$$

Where $f(s)$ is the probability of a given state s is realized, conditional on the good j being shocked and $P_{-j}(s)$ is a vector of the prices of the other goods in this market in this state.

This equation gives a set of first order conditions:

$$\sum_{s|jshocked} f(s|jshocked)\{q_j(p, p_{-j}(s)) + (p - mc_j^S)\frac{\partial q_j(p, p_{-j}(s))}{\partial p}$$

$$+ \sum_{j' \in F, j' \neq j} (p_{j'}(s) - mc_{j'}(s))\frac{\partial q_j'(p, p_{-j}(s))}{\partial p}\} \stackrel{!}{=} 0$$

These first order conditions, information on prices, the frequency of sales and a guess of the marginal costs in the non-shocked states can be used to back out the marginal cost in the shocked state. These form one half of the matrix we invert to recover marginal costs/markups from data, conditional on the frequency of shocks. The other half comes from the required indifference between choosing the regular and sale price when the firm has not received the shock.

We also require an assumption about the retailers information sets and how those relate to the choices they make. We restrict each firm to only consider the mixed strategy in a single product at a time. This will allow us given a guess of the markups of each firm in the unshocked state to find the mixed strategy that each firm plays to hold each other firm indifferent between sale and not in their unshocked state. Consider with out loss of generality the mixed strategy of good i holding firm j's profits equal across sale and not sale. We only need to consider the state where firm j have not received the cost shock. All other firms sale or not sale prices will be unknown to the retailer considering good j and therefore will have to encapsulated in an expectation we denote $\mathbb{E}_{-i,-j}$.

In the mixed strategy equilibrium, α_i^j must be such that:

$$\alpha_i^j \mathbb{E}_{-i,-j}\left[\Pi_j(p_i^S, p_j^S, p_{-i,-j}) - \Pi_j(p_i^S, p_j^R, p_{-i,-j})\right]$$

$$+(1-\alpha_i^j)\mathbb{E}_{-i,-j}\left[\Pi_j(p_i^R, p_j^S, p_{-i,-j}) - \Pi_j(p_i^R, p_j^R, p_{-i,-j})\right] = 0$$

Since we directly observe α_i we can write these equations as functions of data and of unobservables. These equations form another set of linear conditions that we use to recover the marginal costs from observed behavior. In practice this yields as many conditions for each good j as goods the firm does not control. In estimation we average them.

Given data on the frequency of temporary price reductions and a guess of the frequency of the shocks, the mixed strategy is known. Therefore for every market-month we can compute the marginal cost associated with shocked and the unshocked marginal costs for each good conditional on the frequency of the shock, based on the matrix described in section this includes the first order condition for the maximization of the product after the shock, and the indifference condition between the sale price and the regular price for the unshocked firm. This linear system is J equations in J unknowns. We take the first order condition for the choice of the regular price:

At this stage we have enough information to write the profit maximizing first order condition at the beginning of each period solely as a function of data and one set of unobservables, the frequency of the shocks to marginal cost for each firm in each market r_{jmt}. We transform the frequency of the shock as:

$r_{jmt} = \frac{\exp^{\hat{r}_{jmt}}}{1+\exp^{\hat{r}_{jmt}}} * \alpha_{jmt}$

to ensure that r_{jmt} a probability between zero and α_{jmt}, that is to say consistent with the model.

We need to invert the first order conditions for regular price setting in the vector r_{mt}:

$$\begin{aligned}
&\omega_f \frac{\partial \mathbb{E}_{r_{mt}} \pi_f(P^R, r_{mt})}{\partial p^R_{jmt}} \\
&+ \sum_{f' \neq f} \omega_{f'} \frac{\partial \mathbb{E}_{r_{mt}} \pi_f(P^R, r_{mt})}{\partial p^R_{jmt}} \\
&+ \lambda_f \frac{\partial \mathbb{E}_{r_{mt}} \pi^D_f(P^R_{jmt}, P^R_{-jmt}, r_{mt})}{\partial p^R_{jmt}} \\
&- \sum_{f' \neq f} \lambda_{f'} (\frac{\partial \mathbb{E}_{r_{mt}} \pi^D_{f'}(P^D_{f'}, P^R_{-f'}, r_{mt})}{\partial p^R_j} - \frac{\partial \mathbb{E}_{r_{mt}} \pi_{f' r_{mt}}(P^R, r_{mt})}{\partial p^R_j}) = 0
\end{aligned}$$

Where both the expectations and the profit functions through marginal costs depend on the vector of the frequency of the shocks r_{mt}. We recover a $\hat{r}_{jmt}$ for each product market and period, conditional on the profit weights and Lagrange multipliers.

We then compute a residual from a mean model for $\hat{r}_{jmt}$:

$$\hat{r}_{jmt} = \alpha_0^S + \nu_{jmt}^S$$

This ν_{jmt}^S is the main structural residual we recover, it shifts the marginal costs and expected profit functions through the conditions we impose listed above.

In order to generate the sample analogues of the above first order condition several terms are required, firstly we need to solve the deviating firm's problem. To do this we solve for the optimal prices of each product that has not received the cost shock, nor gone on sale, given every other firms prices. We do this in every state and calculate the derivatives given each state to aggregate to the expected derivative. Secondly, we need to consider how changing the regular price will change the sales price that the firm will charge given it has a shock. Finally, the firms internalize that changing regular prices will change the frequency with which they will put the goods on sale through the mixed strategy.

1.4.3 Identification

This section discusses the identification of the various components of our model of supply. We can separately identify the profit weight parameters ω_{ft} from the Lagrange multipliers λ_{ft} because due to the timing assumptions the firms only consider goods that have not received the shock, nor been put on sale in the given period when considering defection. The relative response of the producer to the components of the entire profit function, versus solely those components that it considers for the most profitable deviation separately identify ω_{ft} and λ_{ft}.

We then form moments in ν^S_{jmt} (the random component of the frequency of the shock to marginal cost). We use as instruments the demand conditions that are plausibly exogenous to the supply conditions, we use the average income in each market, the number of products offered in each market, as well as the average fuel cost of competing product and the local preference for competing goods. We weight each summand in the moment condition by the fraction of revenue each firm generates from that product-market pair. We believe these instruments contain useful variation that shift the incentives to deviate, we face an endogenity problem as the prices in each market are determined by equilibrium. We need instruments that shift market prices that are independent of the producer's cost processes. Our choice of instruments follows Berry Haile (2014), while we differ in the specification of costs.

We believe that the frequency of the shock is identified by the relative weight the producer places on the markup of the sale price above the shocked cost. If r_jmt is small than the markup of the mimicking retailer (sale price above unshocked cost) will be have relatively more important. The marginal costs are identified by the behavior of the producers when they receive the shock (the static first order condition) and by their behavior when they do not (the indifference condition between sales and regular price in the mixed strategy).

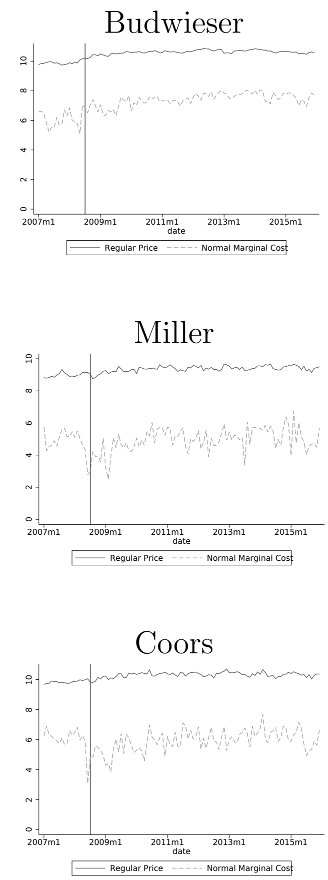
1.4.4 Estimation Results

We present the main results of our estimation of the supply side of the model. We estimate a separate profit weight and Lagrange multiplier for each period in our model. We normalize the profit weights ω_{ft} to sum to one. ($\sum_f \omega_{ft} = 1$). This is a substantive assumption as it implies that all three firms (or two after the Miller-Coors merger) are within the same coalition. We believe, however in this context it is justified as these are the largest players in this market and other research has shown evidence of their collusion.

While some interpretation is possible for these parameters, they have serious short comings. Following on a long history of attempting to estimate "conduct" parameters (Breshnan 1981 for example) or "conjectoral variations", several authors have cast significant doubt on whether such parameters allow meaningful counterfactuals. Corts (1999) suggests that parameters estimated from pooling across different time periods do not reflect the correct marginal trade-offs a firm faces but instead average across different trade-offs. The parameters we estimate come from a single decision horizon for the producers (at least with respect to our modelling assumptions), which partially address this concern. However, the parameters are only consistent with this equilibrium with these primitives, we do not know how the parameters change as the equilibrium changes. This means that we must be very selective in interpretation, as well as in their usage for counterfactuals.

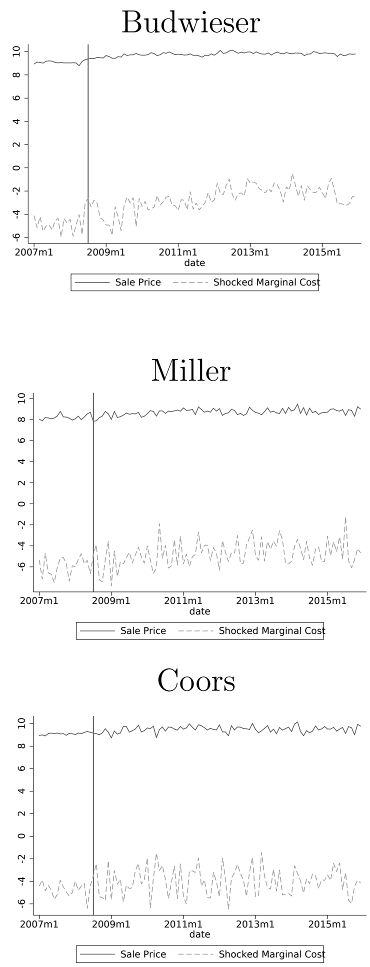
What more easily interpreted, however, is the markups above cost that the firms charge during the periods we have estimated the model. The mean regular prices and unshocked costs, which are computed by taking a weighted by sales average across

Figure 1.3: Regular Prices and Normal Marginal Costs



Note: Weighted average across markets and products for each month and brand. Estimation procedure described in text for marginal costs. Regular prices are taken from monthly product averages of the regular prices computed using the algorithm form Midrigan (2011).

Figure 1.4: Sale Prices and Shocked Marginal Costs



Note: Weighted average across markets and products for each month and brand. Estimation procedure described in text for marginal costs. Sale prices are calculated from monthly product averages of the depth of sales from the differences from regular price, then discounted from average regular prices. Regular prices were computed using the algorithm form Midrigan (2011).

all markets at a given time is presented in Figure 1.3. The markup is the difference between the price (top line) and the cost (bottom line). We also present the sales price and shocked marginal costs in Figure 1.4. The sales prices are lower than the regular price, but the shocked prices are much lower than the unshocked prices. This implies that the markup given the firm has received the shock is much higher than the markup given it has not. Since the merger was consummated in July 2008, we see a large shake up in the competitive environment after that point. We see that the markups and prices rise after that time. The markups for Miller Coors rose by much more than the markups for Budweiser. Relative to Budweiser it appears that Miller-Coors did have some substantial cost reductions.

Somewhat unusually, our estimates of marginal costs are negative in the shocked state on average. We believe this is plausible in our context because the shocks are motivated by supply chain or inventory shocks. In the case that a retailer or distributor has excess inventories they need to either sell them or dispose of them before expiration. In this case we motivate the marginal cost to include not cost of production, but the opportunity cost of holding the excess inventories, as well as the costs of disposal.

While the slightly negative marginal costs are plausibe, the ones we find are too large to be consistent with free disposal. We are endeavoring to examine the source, the demand system may be too inflexible and rationalize the sales only with very large markups that imply negative marginal costs. Additionally, our supply side may not be well identifying the conduct seperately from marginal cost. For these reasons we are exploring a more flexible demand system, and estimating the conduct parameters pooling across time which will allow for unobserved hetrogenity in the costs.

To summarize the direct impact of the merger we compute the averages across the time periods for a before merger, and immediately post merger. We include January 2007 to May 2008 as the pre sample and May 2009 to December 2012. This are the same time periods we use in the difference in difference regressions in Section 1.2. We present these averages in table 1.6. It is apparent from this table that the regular prices rose for each firm, while the marginal cost rose for Budweiser and stayed mostly stable or fell for Miller-Coors. The shocked marginal costs rose nearer to zero, while the sale prices rose. The markup of sale price over shocked costs appears to not have differed as a result of the merger.

1.5 Comparision of Equilibria

That an equilibrium exists with sales is not enough to argue that the producers go on sale for this reason. We need to show that there is some benefit to selecting the sales equilibrium. There are two outcomes we consider: profitability of each firm, and the ease at which the tacitly collusive arrangement can be sustained. The sales equilibrium should be preferable to a non-sales equilibrium in at least one of these two criteria. In this section, we show that for our sample and estimated primitives, the sales equilibrium is preferable in both criteria to a non-sales equilibrium where each firm uses only the observed regular price with certainty.

In order to evaluate the sustainability of the equilibrium we propose, we need both a notion of sustainability, and another equilibrium to compare to ours. We follow the

Table 1.6: Means of main strategic variables:
Pre and Post merger

		Budwieser	Miller	Coors
Regular Price	pre	9.86	8.97	9.83
	post	10.65	9.39	10.37
Markup	pre	3.80	3.91	3.61
	post	3.28	4.39	4.45
Unshocked MC	pre	6.06	5.06	6.22
	post	7.36	5.00	5.92

		Budwieser	Miller	Coors
Sale Price	pre	9.05	8.19	9.08
	post	9.80	8.74	9.56
Markup	pre	13.89	14.12	13.71
	post	12.66	13.45	13.42
Shocked MC	pre	-4.84	-5.93	-4.63
	post	-2.86	-4.71	-3.86

Note: Weighted average across markets and products for each month and brand. Estimation procedure described in text for marginal costs. Sale prices are calculated from monthly product averages of the depth of sales from the differences from regular price, then discounted from average regular prices. Regular prices were computed using the algorithm form Midrigan (2011). We include January 2007 to May 2008 as the pre sample and May 2009 to December 2012 as the post sample.

existing literature in the first point, beginning with Abreu (1986, 1988), which study of these dynamic or repeated games of collusion. This literature has focused on the threshold discount factor. Given the equilibrium, and specification of the defection and punishment, while taking some stance on the firms' beliefs about the future, papers find the discount factor that would make the producers indifferent between collusion and defection. Intuitively, the higher this discount factor the more difficult collusion is to sustain. Recent papers such as Eizenberg and Shillan (2019) use these threshold discount factors to characterize the stability of collusive arrangements.

As discussed in Sullivan (2017) the researcher must take a stance on the producers beliefs about the future flow of profits under both collusion and defection. One stance has been used is that the primitives Θ_t is held to be constant at the time of the decision to defect, firms would then believe that collusive profits today would continue identically if collusion were sustained. The researcher then finds the Nash Bertrand equilibrium[10] of the stage game and conjectures that the firms believe the punishment of the single shot Nash Equilibrium would continue forever if any firm was to defect. With knowledge of the primitives of current stage the researcher has all the information needed to calculate the threshold discount factor:

$$\delta_{tf} = \frac{\pi_{tf}^{defect} - \pi_{tf}^{collusion}}{\pi_{tf}^{defect} - \pi_{tf}^{NB}}$$

that holds each firm f indifferent between defecting and continuing to collude. Profits reflect the total profits aggregated across markets and products of each firm at that time. We follow the existing literature and consider when the discount factor differs by firm, the largest discount factor across firms:

$$\delta_t = \max_f \{\delta_{ft}\}$$

[10]For the primitives we consider, the marginal costs will still be random variables. however, there will be no reason to post a regular price in the first stage. In the Nash Bertrand equilibrium each product will have a price that will be charged when the product gets the shock and a price that will be charged when it does not.

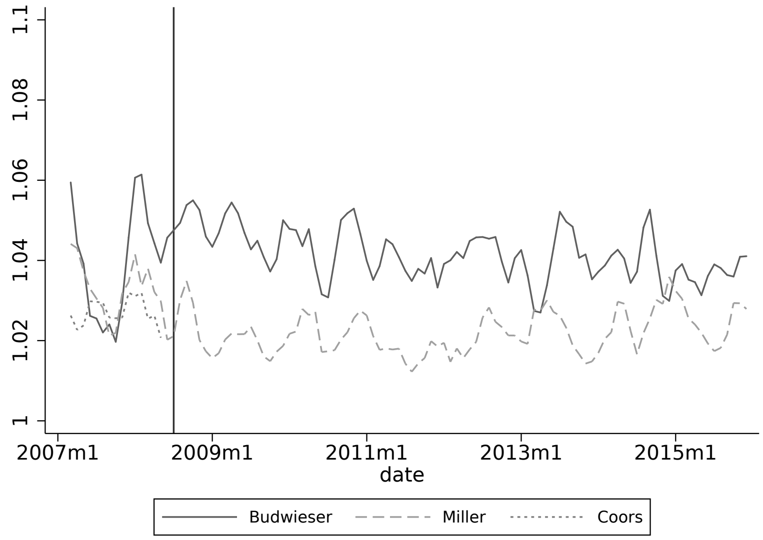
. Sullivan (2017) notes that the producers should internalize that Θ_t evolves through time, as well as the equilibrium strategies that respond to it. In future work we hope to model this directly, in this paper we assume the firms believe that the current equilibrium and profits will continue forever.

We consider for comparison the equilibrium where each firm charges the regular price we observe in the data, and does not ever go on sale.[11] We believe this is a natural equilibrium to consider, using observed prices is the simplest to compute candidate equilibrium. We consider this equilibrium with the same primitives as the sales equilibrium in each period. The strategy is comparable to our sales equilibrium, firms will cooperate by charging the regular price in each period, defection will come in the form of setting optimal prices dependent on the presence of the marginal shock, and punishment takes the same form as the sales game. In fact the Nash Bertrand equilibrium will be the same for each game, making comparison easier. This is because the game has no history dependence beyond the recall of defection.

We compute the per period collusive profit for our sales equilibrium and the no-sales equilibrium. We show the history of the ratio between the sales and no-sales equilibrium profits in Figure 1.5. This number is greater than one when the sales equilibrium is more profitable than no-sales equilibrium. In Table 1.7 we report summary statistics over time for this ratio. In this table we also sum across all firms to show the industry profit is also always larger in the equilibrium that allows sales.

[11] In this section we winsorize the markups we compute at 0 and 20, while there are not many observations that fall outside this range, they make computing new equilibria infeasible. As each object is reported in terms of ratios in this section we believe that our results will not be overly sensitive to other choices of bounds.

Figure 1.5: Comparison of Equilibrium Profit



Note: This graph shows the 3 month moving average of the ratio between collusive profits in our sales equilibrium and the no sales equilibrium. A number greater than one reflects the fact that the firms generate more profit in the sales equilibrium. Calculation described in text.

We have established that the sales equilibrium is more profitable than the non-sales equilibrium we consider. Next, we turn our attention now to the sustainability of collusion. In Table 1.8 we report the mean and median across time for the minimum discount factor that supports the each of the sales and no-sales equilibrium. The sales equilibrium has on average a lower level of the minimum discount factor , we interpret this as illustrating that the no-sales equilibrium is harder to sustain. In figure 1.6 we show the three month moving average of the maximum across firms of the minimum discount factor. Clearly the no sales equilibrium has a larger required

Table 1.7: Summary Statistics: Ratio of Profits

	Average	Min.	Max.
Aggregate	1.03	1.01	1.05
Budweiser	1.04	1.02	1.08
Miller	1.02	1.01	1.05
Coors	1.03	1.01	1.04

Note: This table shows the ratio between the collusive profit for the sales equilibrium to the no-sales equilibrium. Aggregate is computed by summing across all the firms in the pricing coalition.

discount factor in most periods. In addition it appears the minimum discount factor after the merger, this might be interpreted as the firms now more able to cooperate and therefore able to raise profits by choosing a more difficult equilibrium to sustain.

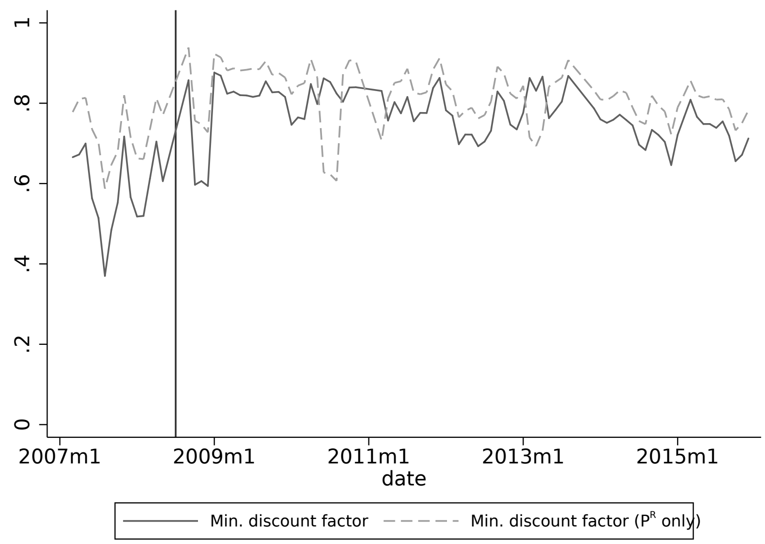
Table 1.8: Summary Statistics: Discount Factor

	Min. Discount Factor:	
	Sales Eqm	No Sales Eqm
Mean	0.74	0.80
Median	0.80	0.83

In order to show the origin of these results, we show in Table 1.9 the ratios of defection profits, and collusive profits to the Nash Bertrand profits for Miller-Coors in March 2009. Here we see that the sale equilibrium has a higher collusive profit, while the no sale equilibrium has a larger profit from defection. The following formula holds for the discount factor:

$$\frac{\delta_f}{1-\delta_f} = \frac{\frac{\pi_{tf}^{defect}}{\pi_{ft}^{NB}} - \frac{\pi_{ft}^{C}}{\pi_{ft}^{NB}}}{\frac{\pi_{ft}^{C}}{\pi_{ft}^{NB}} - 1}$$

Figure 1.6: Comparison of Sustainability



Note: This graph shows the 3 month moving average of the maximum across firms of the minimum discount factor that makes each equilibrium sustainable. A larger number means a less sustainable equilibrium. Calculation described in text.

Where π_{tf}^{defect} is the defection profit, π_{ft}^{NB} is the Nash Bertrand profit, and π_{ft}^{C} is the collusive profit. All else equal with a larger collusive profit the firm will have a larger punishment from defection, and a smaller incentive to defect. Additionally, all else equal the larger the defection profit the greater the incentive to defect. Table 1.9 is representative of the source of the result that the sale equilibrium is more sustainable.

Table 1.9: Source of sustainability: Profits

	Defection Profit to NB Profit	Collusive Profit to NB Profit	Discount Factor
Sale Eqm	1.48	1.12	0.75
No Sale Eqm	1.54	1.09	0.83

Note: This table reports ratios of profits to Nash Bertrand profit for Miller-Coors in March 2009.

There are other potential equilibrium we could consider, in fact there are many even with in the set of Pareto optimal equilibria. In particular we believe examining the equilibrium that delivers the same collusive profits but without sales would allow us to further investigate the effects of allowing sales on the stability of collusion. Alternatively, we could consider an equilibrium with equal sustainability and examine the profitability.

We conclude that not only is the sales equilibrium more profitable than an empirically natural comparison equilibrium, but it is more sustainable than the same equilibrium. We believe that not do sales allow the firms to take advantage of opportunities in the form of price reductions, but also that the price reductions relieve the pressure to defect making the equilibrium easier to sustain.

1.6 Conclusion

In this paper we show that considering temporary price reductions to our understanding of competition and collusion adds not only a real world feature but important information for the inference in the competitive state of a given market. We have also compared the equilibrium that allows firms to put their products on sale to an equilibrium where they cannot. We find that the no sales equilibrium has lower profit, and is more difficult to sustain. Sales allow some flexibility in the tacit collusive arrangment, without lowering the punishment needed to sustain high prices.

CHAPTER II

Does Product Revenue Matter for Price Setting and Monetary Policy Transmission?

2.1 Introduction

The macroeconomic literature on price setting has mostly ignored variation in product revenue, and its effect on price setting behavior and monetary policy transmission. There is little evidence in either direction, as to whether revenue should or should not influence such outcomes. In this paper, we examine the relationship between the price and the revenue of a product, and its consequences for monetary policy. We find that revenue variation across products and through time directly affects price setting decisions and the transmission of monetary policy. In other words, revenue is not *neutral* in the firm's pricing problem.

Many studies treat revenue as neutral and assume away revenue variation in the price setting problem. In contrast, we find evidence of revenue non-neutrality in price setting. We find a positive relationship between product revenue and the probability of adjustment, as well as a negative relationship between product revenue and the absolute size of adjustment in the data. Using a menu cost framework, we demonstrate that these facts imply non-neutrality of revenue in the pricing problem.

This non-neutrality has important consequences for monetary policy transmission. Under non-neutrality, monetary policy shocks have heterogeneous effects on prices depending on product revenue. We show that the responsiveness of prices to a monetary shock increases in revenue under non-neutrality; both empirically, and in the class of menu cost models consistent with our empirical findings. Therefore, the degree of monetary transmission is directly affected by the treatment of revenue variation in menu cost models. In addition, the non-neutrality of product revenue can generate a counter-cyclical force that strengthens the real effect of monetary policy during recessions.

First, using a theoretical framework akin to Caballero and Engel (2007), we illustrate how revenue variation affects pricing behavior. In menu cost models, the relationship between price setting behavior and revenue can be summarized by the relationship between revenue and the menu cost. For neutrality to hold, the menu cost must scale one-for-one with product revenue. In such a case, there would be no correlation between product revenue and neither the probability nor the absolute size of price adjustment. If the menu cost increases less then proportionally with revenue, then the probability of price adjustment should increase, and the size of adjustment should decrease with product revenue. In this case, revenue variation matters for the real effect of monetary policy.[1]

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[1]We note that studies that attempt to measure menu costs directly usually suggest that menu

We establish a theoretical relationship between product revenue and the response of prices to monetary shocks. We derive expressions for both the intensive margin component of price responsiveness and the extensive margin component, and its dependence on product revenue. We show that the relationship between revenue and the price response to a monetary shock has the same sign and is proportional in magnitude to the relationship between product revenue and the probability of price adjustment, as long as it is more likely for the firm's actual price to be close to its desired price than far from it.

Next, we test for revenue neutrality using our predictions on the relationships between product revenue and price adjustment. Using scanner data of retail goods, we find that the probability of price adjustment increases with product revenue, and the average size of price adjustment decreases with product revenue. These relationships are robust to various controls and are driven not only by cross-sectional differences in product or retailer characteristics but also by the variation in revenue of a product across time. In addition, we show that the responsiveness of prices to high frequency federal funds rate shocks also increases with product revenue. The average total response of prices of products in the lowest quantile of revenue is 19% of that of products in the highest quantile of revenue after 12 months and 26% after 18 months. To the best of our knowledge, these facts are new to this paper.[2]

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costs do not scale perfectly with product revenue (Zbaracki et al., 2004, Levy et al., 1997).

[2]Some papers have noted that there is a relationship between firm size and price changes, including notably, Goldberg and Hellerstein (2011). Bhattarai and Schoenle (2014) insinuate that larger firms change price more frequently, as larger firms are more likely to sell more goods. However, these results focus on the characteristics of price setting in the cross-section at the firm level. Our

Taken together, our theoretical and empirical findings imply revenue non-neutrality and heterogeneity across products in the response to monetary shocks. Therefore, to study the quantitative implications of revenue variation on the real effect of monetary policy, we utilize a menu cost model augmented to match the behavior of the revenue distribution across the business cycle.

First, we verify that revenue variation generates large differences in the responsiveness of prices to a monetary shock across products as we have claimed. The prices of products with higher revenue are more responsive to monetary shocks when revenue is non-neutral, whereas, in a revenue neutral economy, the difference is minimal. We find that in our model, the price response can differ by as much as twofold across products with different levels of revenue due to non-neutrality. This accounts for approximately 40% of the difference found in our empirical results. The heterogeneous response of prices leads to a large difference in the aggregate output response to a monetary shock between revenue neutral and non-neutral economies. Output response is 50.6% larger in the revenue neutral economy.

Second, we show that systematic shifts in the revenue distribution introduce a counter-cyclical force to the real effect of monetary policy. Because revenue is greater during high output states, and more so for high revenue products, the price response to a monetary shock is larger during expansions. The size of this effect is modest, as the cumulative effect of monetary policy on output increases by 8.6% during recessions through this mechanism in our model. When we include counter-cyclical

results suggest a direct relationship between revenue and price adjustment at the product level that holds both in the cross-section of products and across time.

volatility shocks, the mechanism that Vavra (2014) finds generates pro-cyclical effects, the two forces cancel out and the magnitude of the real effect of monetary policy is invariant across the business cycle.

In contrast to our results, many price setting models make assumptions that enforce revenue neutrality in the price setting problem. In time-dependent models, such as standard New Keynesian Calvo pricing or Rotemberg pricing models, price setting decisions are revenue neutral. The timing of price changes is exogenous to the firm, and desired prices are functions of only current and future marginal costs and other aggregates.

Many recent papers with state-dependent pricing also assume revenue neutrality, mostly to facilitate analytical tractability or computation. For example, Gertler and Leahy (2008) assume that the menu costs scale with firm size in order to derive analytical expressions for a dynamic Phillips curve. Alvarez and Lippi (2014) and Alvarez et al. (2016) directly assume that firm loss from sub-optimal prices depends only on the price gap, which allows them to derive analytical solutions. Midrigan (2011), on the other hand, assumes that idiosyncratic demand shocks exactly offset productivity shocks such that revenue is normalized to reduce the computational burden of solving his model. However, as our paper shows, the treatment of product revenue has important implications for both price setting behavior, both at the microeconomic level and for the real effect of monetary policy at the macroeconomic level, casting doubt as to whether the assumption of revenue neutrality is truly innocuous.

The heterogeneous price response that the non-neutrality of revenue entails has several substantive implications. First, heterogeneity in the response of prices across products offers insight into the nature of menu costs and the monetary policy transmission mechanism. For example, our findings suggest that smaller firms with low revenue products are less willing to adjust their prices due to comparably large adjustment costs. This may explain why small firms fail to be well informed about aggregate inflation and monetary policy (Kumar et al. 2015) and suggest that monetary policy works largely through small firms and low revenue products rather then through high revenue firms. As such, understanding hetrogenities in the transmission of monetary policy can be integral to optimal policy design.

Furthermore, the heterogeneity in the response of prices across products of varying revenues can have distributional consequences. For example, Cravino et al.(2020) show that high income households consumer price indices are one-third less responsive to monetary policy than those of middle-income households. Kaplan and Schulhofer-Wohl (2017) find large cross-sectional dispersion in the household inflation rate stemming mostly from variation in prices paid for the same types of goods. Our results provide a potential mechanism behind these findings, through the variation in products and stores different households frequent.

Lastly, heterogeneity in the policy responsiveness of prices across products has important consequences for our understanding of *monetary* non-neutrality. For example, Nakamura and Steinsson (2010) find that accounting for heterogeneity in the frequency and median size of price adjustment across different sectors of the economy increases the degree of monetary non-neutrality in menu cost models.[3] Alvarez

[3]Carvalho (2006) finds that in Calvo models the degree of monetary non-neutrality is convex in

et al. (2016) argue that the ratio of kurtosis to the frequency of price changes is a sufficient statistic for the real effect of monetary shocks. However, accounting for revenue non-neutrality in each of these analyses may alter their conclusions. The sizable differences in the responsiveness of aggregate output between revenue neutral and non-neutral economies imply that accounting for the effect of revenue on price setting and matching the revenue distribution is vital to understanding the degree of monetary non-neutrality. Additionally, heterogeneity in individual responses can have an effect on the degree of state-dependence of the aggregate response to a shock.

Our work contributes to a growing literature on the heterogeneous effects and distributional consequences of monetary policy. For example Beraja et al. (2018) find regional heterogeneity in monetary policy effects due to variation in the levels of housing equity. Additionally, Wong(2019) finds heterogeneous effects of policy across the life-cycle due to the differing exposure to mortgage rates. Auclert (2019) documents heterogeneity in earnings, balance sheet exposure, and interest rate exposure and their effect on monetary policy transmission. Coibion et al.(2017) show that monetary policy shocks have contributed to the historical volatility of income and consumption inequality in the United States.

This paper is also closely related to the large literature using microdata to evaluate price changes pioneered by Bils and Klenow (2004), Nakamura and Steinsson (2008),

the frequency of price change and thus heterogeneity in the frequency of price adjustment through the Calvo parameter increases the degree of monetary non-neutrality relative to those calibrated to the average frequency of price change. Nakamura and Steinsson (2010) find that in menu cost models this result depends on the underlying differences that cause the heterogeneity. In their model, the effect is in particular reliant on the relationship between the frequency and size of price changes across sectors.

and Klenow and Kryvtsov (2008). Various papers, such as Golsov and Lucas (2007) and Midrigan (2011), have shown that accurately reflecting price setting behavior as documented in the empirical literature has important implications monetary non-neutrality.[4] Our paper adds to this literature by studying the relationship between product revenue and price setting behavior.

A number of papers have pointed out that firms with multiple products appear to make pricing decisions based on the totality of their products. For example, Lach and Tsiddon (1996, 2007) provide evidence showing synchronization of price changes within a given firm, and Bhattarai and Schoenle (2014) find that firms selling more goods adjust their prices more frequently and by smaller amounts. On the theoretical side, Midrigan (2011) and Alvarez and Lippi (2014) have shown that accounting for multi-product firms would, in general, increase aggregate price stickiness. While our paper focuses on a single product setting, the general results of our paper are complementary with this line of work. Incorporating our findings into a multi-product firm environment would be straightforward. Firms would simply consider the revenue of the totality of their products in their pricing decisions, and our main thesis would remain unaltered.

Our results regarding the state-dependence of monetary policy are closely related to Vavra (2014). Vavra finds that the average frequency of price adjustment and the cross-sectional standard deviation of the size of price changes are counter-cyclical. He

[4]Other papers that study the relationship between price setting behavior at the micro-level and aggregate fluctuations include Alvarez and Lippi (2014), Alvarez et al. (2016), Burstein and Hellwig (2007), Caballero and Engel (2007), Caplin and Spulber (1987), Gertler and Leahy (2008), Midrigan and Kehoe (2015), and Nakamura and Steinsson (2010) among others.

argues that, if this is driven by volatility shocks to idiosyncratic productivity, the real effects of monetary policy will be weaker in recessions. However, state dependence of the effects of monetary policy is not a settled issue. For example, in contrast, Santoro et al. (2014) show that loss aversion can imply stronger monetary policy transmission in recessions.

In Section 2.2 we derive the relationship between product revenue and price setting behavior and monetary policy using a simple analytical framework. In Section 2.3, we test these relationships empirically. In Section, 2.4 we use a quantitative menu cost model to demonstrate the implications of our results on the real effect of monetary policy. Section 5 concludes.

2.2 Revenue And Price Setting

In this section, we present our framework in which we derive the relationship between product revenue and the price setting behavior of firms. We illustrate our point using a static menu cost problem of a firm. This allows us to demonstrate the mechanism behind why revenue matters in a clear and analytically tractable way. We present expressions that describe the relationship between price setting behavior and product revenue that can be tested empirically. We derive expressions for the implications of these relationships for monetary policy transmission.

2.2.1 Analytical Results

We first solve the firm's price setting problem to demonstrate the relationship between revenue and price setting. Consider a static problem of a firm with constant marginal cost facing a demand curve with constant elasticity of demand ϵ. To derive the optimal price, the firm solves the following problem,

$$\max_p \quad \pi(p) = (p - mc)y(p) \tag{2.1}$$

where p is the firm's price, mc is its marginal cost, and $y(p)$ is the demand schedule for the firm's product. The optimal price for this firm p^* can be solved as,

$$p^* = \frac{\epsilon}{\epsilon - 1} mc.$$

A second order approximation of the profit function π around p^* yields,

$$\pi(p) \approx \pi(p^*) + \frac{1}{2}\pi^{*''}(p - p^*)^2$$

where $\pi^{*''} = (1 - \epsilon)(\frac{y(p^*)}{p^*})$. We can then express the loss of a firm from having suboptimal price p as

$$L = \pi(p^*) - \pi(p) = -\frac{1}{2}\pi^{*''}(p - p^*)^2 > 0.$$

Suppose that the firm inherits some price p and the firm must pay a small menu cost in order to change its price. In order to demonstrate the role of revenue in price setting, we allow the menu cost to be a function of the firm's optimal desired revenue $rev^* \equiv p^*y(p^*)$. Given rev^*, a firm will choose to change its price only if the loss from suboptimal price L exceeds the menu cost $b(rev^*)$, that is, if

$$L = \frac{1}{2}(\epsilon - 1)p^* y(p^*)\Big(\frac{p - p^*}{p^*}\Big)^2 > b(rev^*). \tag{2.2}$$

Rearranging equation (2.2) and utilizing the approximation that $ln(\frac{p}{p^*}) \approx (\frac{p-p^*}{p^*})$ around zero, we can solve for the inaction region of the firm to get,

$$\Big|lnp - lnp^*\Big| < \sqrt{\frac{2b(rev^*)}{(\epsilon - 1)rev^*}}. \tag{2.3}$$

If the firm's inherited price p is adequately close to its desired price p^* as described by equation (2.3), the firm will not change its price. The range of inaction, expressed as percent deviations from the optimal price, is a function of desired revenue rev^*.[5]

For analytical tractability we assume that the menu cost has the functional form $\bar{b} \cdot (rev^*)^k$ where $\bar{b}$ is some constant. This functional form assumption allows us to parsimoniously capture the relationship between revenue and price setting with one scaling parameter k. If $k > 1$, the menu cost of the firm increases at a rate faster then revenue, and the inaction region grows larger as revenue increases. With $k < 1$ the opposite is true. If $k = 1$, the menu cost is fixed in relation to revenue and revenue drops out of equation (2.3). Thus revenue plays no role in determining whether firms adjust their price and is *neutral* if $k = 1$.

We denote the price gap between the inherited and optimal price of the firm as $x \equiv lnp - lnp^*$. Suppose that the probability distribution of this price gap over

[5]In addition, the inaction zone decreases with the elasticity of demand and is increasing in menu costs.

time follows the distribution $F(x)$.[6] Then, we can derive the expressions for the probability of price adjustment and expected absolute size of adjustment conditional on change as,

$$prob(rev^*) = F(-\zeta(rev^*)) + (1 - F(\zeta(rev^*))) \tag{2.4}$$

$$size(rev^*) = \frac{1}{prob(rev^*)}\Big\{ \int_{-\infty}^{-\zeta(rev^*)} (-x)f(x)dx + \int_{\zeta(rev^*)}^{\infty} xf(x)dx\Big\} \tag{2.5}$$

where $prob(rev^*)$ is the probability of adjustment conditional on revenue and $size(rev^*)$ is the expected absolute size of adjustment conditional on revenue. $\zeta(rev^*) = \sqrt{\frac{2\bar{b}\cdot(rev^*)^{k-1}}{(\epsilon-1)}}$ is the distance between the optimal price to the edges of the inaction region. We can derive the relationship between these two statistics and log revenue by differentiating equations (2.4) and (2.5) with respect to log revenue:

$$\frac{\partial prob(rev^*)}{\partial ln(rev^*)} = \frac{1-k}{2} \cdot \zeta(rev^*)[f(-\zeta(rev^*)) + f(\zeta(rev^*))] \tag{2.6}$$

$$\frac{\partial size(rev^*)}{\partial ln(rev^*)} = \frac{\partial prob(rev^*)/\partial ln(rev^*)}{prob(rev^*)}\Big\{\zeta(rev^*) - size(rev^*)\Big\}. \tag{2.7}$$

The sign of equation (2.6) is determined by the parameter k. If $k > 1$, it is less than zero and if $k < 1$, it is greater then zero. If $k = 0$ equation (2.6) is exactly zero. The sign of equation (2.7) is also determined by k. The sign of equation

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[6] We assume that the distribution F is independent of the firm's revenue. This assumption is not exactly true, most notably due to our claim that product revenue directly affects price setting decisions. However, our assumption of independence can be thought of as assuming that the indirect effects through differences in the distribution of price gaps across revenue is small compared to the direct effect through the movements in the inaction region. Our numerical simulations from the dynamic quantitative model in Section 2.4 support this assumption.

(2.7) is opposite that of equation (2.6) because $size(rev^*)$ is greater than $\zeta(rev^*)$ by construction. This is always true unless $k = 1$, in which case equation (2.7) should also equal zero.

The sign of the relationships in equation (2.6) and (2.7) can be verified empirically. Notice that while the expressions depend on revenue, their signs do not. Because the signs are unchanged by revenue, the sign of the weighted average of these expressions will be equal to the sign of the individual equations. Thus the signs of $\int \left(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\right) g(rev^*) drev^*$ and $\int \left(\frac{\partial size(rev^*)}{\partial ln(rev^*)}\right) g(rev^*) drev^*$, where $g(rev^*)$ is the density of the cross-sectional revenue distribution, will allow us to determine whether revenue variation matters for the price setting problem.

Recall that the price setting problem is revenue neutral only if $k = 1$, which would imply that the values of both $\frac{\partial prob(rev^*)}{\partial ln(rev^*)}$ and $\frac{\partial size(rev^*)}{\partial ln(rev^*)}$ are zero. In Section 2.3, we find that the empirical sign of $\int \left(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\right) g(rev^*) drev^*$ is positive, and $\int \left(\frac{\partial size(rev^*)}{\partial ln(rev^*)}\right) g(rev^*) drev^*$ is negative, consistent with $k < 1$. This suggests that menu costs are relatively fixed in proportion to product revenue.

This result is consistent with studies that attempt to measure menu costs directly. For example, Zbaracki et al. (2004) show that the managerial cost of price adjustment which, presumably, is relatively fixed in proportion to revenue, is 6 times larger than the physical cost for a U.S. industrial manufacturer.[7] Levy et al. (1997), measure the physical costs of changing prices for a U.S. supermarket chain. They find that most of their costs are fixed costs, such as the cost of preparing and changing a shelf

[7]They also find that costs of informing and negotiating with customers are even greater, approximately 20 times larger than physical costs. The relevance of customer costs in our setting, however, is less clear as the price of retail items are generally non-negotiable.

price tag, verification costs, and supervision costs.

2.2.2 Monetary Policy Transmission

We now derive a testable prediction for relationship between product revenue and the degree of responsiveness of prices to a monetary shock. Building on the previous section, suppose that firms now face a monetary policy shock Δm. Let lnp^* and $ln\hat{p}^*$ denote respectively, the desired price of the firm before and after the monetary shock. As in Caballero and Engel (2007), the desired optimal price of individual firms changes as follows:[8]

$$\Delta lnp^* = ln\hat{p^*} - lnp^* = \Delta m. \tag{2.8}$$

Denote $x \equiv lnp - lnp^*$ and $\hat{x} \equiv lnp - ln\hat{p}^*$ as the price gap before and after the monetary shock. Then, the price gap after the monetary shock is,

$$\hat{x} = x - \Delta m.$$

The expected price response for a firm with a given level of revenue $\mathcal{F}(rev^*)$, is defined as the expected percent change in price as a ratio of the monetary shock, to

[8]This equation is analogous to Caballero and Engel's (2007) specification on pg.112. The idiosyncratic shocks often utilized to generate price adjustments are abstracted into the distribution of price gaps F. Equation (2.8) is consistent with many menu cost models such as the quantitative dynamic model in Section 2.4.

an arbitrarily small shock:

$$\mathcal{F}(rev^*) = \lim_{\Delta m \to 0} \Big(\int \frac{\Delta lnp(x, \Delta m; rev^*)}{\Delta m} f(x)dx \Big). \tag{2.9}$$

Equation (2.9) can be expressed as the expected sum of price changes for prices that are outside the inaction region as follows:

$$\int \Delta lnp(x, \Delta m; rev^*) f(x)dx = \int\limits_{\zeta(rev^*)+\Delta m}^{\infty} -(x - \Delta m) f(x)dx$$
$$+ \int\limits_{-\infty}^{-\zeta(rev^*)+\Delta m} -(x - \Delta m) f(x)dx. \tag{2.10}$$

Price adjustment is zero for inherited prices inside the inaction bands, while the price change for firms outside the inaction bands is equal to the negative of the price gap $-\hat{x} = -(x - \Delta m)$. In addition, the inaction bands themselves adjust in relation to the original distribution of price gaps $f(x)$ in response to the monetary shock.

We derive the explicit expression for equation (2.9) from equation (2.10) by differentiating equation (2.10) with regard to Δm and taking the limit of Δm to zero. The expression for the expected price response to an arbitrarily small monetary shock is as follows:

$$\mathcal{F}(rev^*) = \mathcal{A}(rev^*) + \mathcal{E}(rev^*)$$

where

$$\mathcal{A}(rev^*) = F(-\zeta(rev^*)) + (1 - F(\zeta(rev^*))) = prob(rev^*) \tag{2.11}$$

$$\mathcal{E}(rev^*) = \zeta(rev^*)[f(-\zeta(rev^*)) + f(\zeta(rev^*))] = \frac{2}{1-k} \cdot \frac{\partial prob(rev^*)}{\partial ln(rev^*)}. \tag{2.12}$$

$\mathcal{A}(rev^*)$ is the intensive margin component and $\mathcal{E}(rev^*)$ the extensive margin component of the price response.

As defined by Caballero and Engel (2007), the intensive margin refers to the increase in the size of price changes of firms that would have adjusted anyway, with or without the shock. The expression for the intensive margin is equal to the probability of adjustment given in equation (2.4), as originally shown by Caballero and Engel. This is because the price change induced by the monetary shock for firms that adjust with or without the shock is equal to the size of the shock, so the expected price response is determined by the probability of adjustment.

The extensive margin captures the price change from firms whose adjustment is triggered by the monetary shock. This applies to firms that lie at the edges of the inaction bands. While the probability of being at the edge of the inaction region is small, the size of price change for triggered firms is large. Hence the extensive margin effect can be potentially large. We find that the expression for the extensive margin is equal to the coefficient measuring the relationship between the probability of adjustment and product revenue given in equation (2.6), multiplied by a factor of $\frac{2}{1-k}$. This expression for the extensive margin is new to this paper.[9]

[9] We note that the quantitative magnitude of the extensive margin has been a point of contention

We derive the relationship between product revenue and price response by taking derivatives of $\mathcal{A}, \mathcal{E}$, and $\mathcal{F}$ with respect to log revenue. First, one can see the following for the intensive margin,

$$\frac{\partial \mathcal{A}(rev^*)}{\partial ln(rev^*)} = \frac{\partial prob(rev^*)}{\partial ln(rev^*)}. \tag{2.13}$$

Thus, the relationship between the intensive margin and product revenue is equal to that of the relationship between the probability of adjustment and revenue. This is because as revenue increases the probability of adjustment increases and the additional firms that adjust through the intensive margin effect do so by the size of the monetary shock.

The extensive margin has the following relationship with revenue,

$$\frac{\partial \mathcal{E}(rev^*)}{\partial ln(rev^*)} = -\Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)\Big[1 + \zeta(rev^*)\frac{f'(\zeta(rev^*)) - f'(-\zeta(rev^*))}{f(\zeta(rev^*)) + f(-\zeta(rev^*))}\Big]. \tag{2.14}$$

If we assume symmetry of density f, we can further simplify equation (2.14) as,

$$\frac{\partial \mathcal{E}(rev^*)}{\partial ln(rev^*)} = \Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)\Big[-1 + \zeta(rev^*)\Big(\frac{-f'(\zeta(rev^*))}{f(\zeta(rev^*))}\Big)\Big]. \tag{2.15}$$

in the literature. While much effort has been devoted to measuring the size of the extensive margin effect using indirect methods (for example Luo and Villar, 2017, Alvarez et al., 2016), the difficulty in direct measurement has prolonged the debate. Our framework sheds new light on this debate. In Section 2.3, we provide estimates for the revenue weighted average of $\frac{\partial prob(rev^*)}{\partial ln(rev^*)}$ across firms in the range of $0.011 \sim 0.024$. In Appendix B, we estimate the value of $k = 0.301$, using a parametric model based on the theoretical analysis. The average frequency of adjustment in our sample is 6.7%. These estimates suggest that the extensive margin component of price response is roughly between half to the full size of the intensive margin component. This result aligns more closely with the smaller values suggested by Midrigan (2011) and Alvarez et al. (2016) than the larger values suggested by Golosov and Lucas (2007) and Vavra (2014).

The intuition behind this result is as follows. As revenue increases the inaction bands move closer to the desired price and the marginal firms that are triggered by the monetary shock adjust by a smaller amount, decreasing the price response. This is captured by the first term (-1) in $[-1 + \zeta(rev^*)\frac{-f'(\zeta(rev^*))}{f(\zeta(rev^*))}]$. The term $\zeta(rev^*)\Big(\frac{-f'(\zeta(rev^*))}{f(\zeta(rev^*))}\Big)$ represents the change in the density of firms at the edges of the inaction band. If f' is negative, as is often the case, then the expected price response increases as the probability of being near the edge of the inaction band increases. The term $\Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)$ is the scaling factor.

Then, the relationship between the response of prices to monetary policy and revenue can be derived as follows:

$$\frac{\partial \mathcal{F}(rev^*)}{\partial ln(rev^*)} = \Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)\zeta(rev^*)\Big(\frac{-f'(\zeta(rev^*))}{f(\zeta(rev^*))}\Big). \tag{2.16}$$

The negative effect in the expression for the extensive margin cancels out with the intensive margin, and only the distributional effect of the extensive margin remains. Thus, equation (2.16) suggests that the relationship between the response of prices to monetary policy and revenue has the same sign as the relationship between probability of adjustment and revenue as long as f is downward sloping (f' is negative) as one moves further away from the desired price.

Our findings suggest that it is important to verify the role of revenue variation in the price setting problem. Not only does revenue variation play a critical role for microeconomic price setting behavior, important macroeconomic implications are determined by the presence of revenue variation in the price setting problem as well. If revenue is non-neutral ($k < 1$), products with higher levels of revenue are likely to be more responsive to monetary policy. This implies cross-sectional heterogeneity in the response to monetary policy.

It also suggests that the response of the aggregate price will be larger if revenue is non-neutral compared to the neutral case. Conversely, the response of output will be smaller with non-neutrality. This is due to the fact that high revenue products that are more heavily weighted in the determination of the aggregate price will be more responsive to monetary shocks. This may be partially offset but the decrease in the responsiveness of low revenue products, but low revenue products constitute only a small fraction of the aggregate price. Therefore, it maybe necessary to incorporate revenue non-neutrality into models that attempt to quantify the magnitude of monetary transmission.

Our results also imply that changes in the revenue distribution over the business cycle may lead to state-dependence in monetary policy transmission. With non-neutrality, the level and variance of the revenue distribution play a critical role in the transmission of monetary policy. The variance matters because an increase in the variance of the revenue distribution will increase the aggregate price response due to the fact that high revenue products are more heavily weighted in the determination of the aggregate price.

We believe that the results of Sections 2.2.1 and 2.2.2 are robust to various extensions, for example accounting for multi-product firms. In Appendix B, we re-derive the equations for the case where firms are subject to exogenous adjustment hazards in addition to the menu cost mechanism. As long as the exogenous adjustment hazard itself is not a function of product revenue, the equations governing the relationships between product revenue and price setting do not change. In the example of multi-product firms, unless there is a systematic relationship between a product's revenue and the number of products offered by it's price setter across time, our results would remain robust.

While we believe that our results from a static framework are excellent approximations of a fully dynamic model, we verify our theoretical results within a dynamic framework.[10] The same applies to the assumption that the effect of revenue on the distribution of price gaps do not alter our results. In Section 2.4, we utilize a quantitative dynamic general equilibrium menu cost model to generate the relationships between revenue, price setting, and monetary policy transmission for values of k consistent with our empirical findings and compare the results with a model where revenue neutrality holds. We find that the theoretical analysis of this section holds up well in a fully dynamic model.

2.3 Evidence On Revenue And Price Setting

In this section, we test our theoretical predictions regarding the relationship between price setting and revenue. We present empirical evidence showing that (1) the probability of price adjustment increases with revenue and that (2) the average size of price adjustment is decreasing in revenue. We also present evidence showing that

[10] Elsby and Michaels (2019) show that with small menu costs and two sided adjustment, optimal policy triggers of the static problem are close approximations of the dynamic problem. Dixit (1991), Alvarez and Lippi (2014), and Alvarez et al. (2016) derive optimal policy triggers in a dynamic model, although with limited equilibrium interactions. Their solutions add a multiplicative term to our expression for the inaction region, proportional to the volatility of idiosyncratic shocks.

(3) the responsiveness of prices to a monetary shock is increasing in product revenue.

2.3.1 Data

We use retail scanner data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The scanner dataset includes information on weekly prices, quantities sold, and various product and store characteristics beginning in the year 2006. Over 90 retail chains across all US markets participate in providing information on over 2.6 million UPCs,[11] 1,100 product categories and 125 product groups. The entire data set covers over half of the total sales volume of US grocery and drug stores and above 30 percent of all US mass merchandiser sales volume.

The dataset is large with over a hundred billion observations, making it computationally intractable to use in its entirety. For this reason, we randomly choose a sample of 30 product categories and 34 markets on which we conduct most of our analysis.[12] Nevertheless, even when using this subset of the available data, our coverage of products and markets is comparable and often greater than most studies that utilize retail scanner data. Our sample covers 18,612 different stores, 76 different retail chains and 31,746 different UPCs.

As is standard in studies using micro price data, we focus on "regular" prices and

[11] A UPC (Universal Product Code) is a unique identification number assigned to a retail item.

[12] A product category is a finely defined subset of products defined by The Nielsen Company. Examples include canned tuna, canned fruit and household cleaners. A market is a designated market area defined by The Nielsen Company, which correspond approximately to a metropolitan statistical area (MSA). The full list of product categories and markets in our sample is provided in Appendix B.

price changes, excluding temporary sales. Since not all sales are directly flagged in our dataset, we use the algorithm developed by Midrigan (2011) and Midrigan and Kehoe (2015) to compute regular prices. We compute the regular price as the modal price in an 11-week window surrounding a particular week provided the modal price is used sufficiently often.[13] We define a price change as any change in regular price greater than 1% in magnitude.

Our primary unit of analysis is a product. We define a "product," as a unique UPC-retailer-market combination. Thus, a two-liter bottle of Coca Cola from a retailer sold in the New York market would be considered a separate product from a two-liter bottle of Coca Cola sold in LA by the same retailer. For some products, there can be large random swings in revenue from week to week and occasionally there will zero sales over a week. To address these concerns, we aggregate the data up to monthly frequency. We thus compute product revenue as the total sales of each UPC each month within a market for each retailer. This aggregation has the added benefit of easier comparison of our results to previous studies of price setting behavior, which are usually conducted at monthly frequency.[14]

As our definition of a product indicates, we treat price setting decisions as being made at the retailer-market level for each UPC item separately. While we find some

[13] A detailed description of the algorithm we use to compute regular prices can be found in the appendix of Midrigan (2011).

[14] Several papers have noted that changes in price within a week can cause spurious dispersion in prices. We believe that we are tracking economically relevant changes in prices and revenue and not statistical artifacts of data collection because we exclude small price changes and disregard temporary price changes. In addition aggregation of changes to the monthly level also helps mitigate the effect of spurious changes.

variation in the timing of price changes within the UPC-retailer-market, i.e. at the store level, much of the variation is between retailers and markets. Additionally, DellaVigna and Gentzkow (2019) find that most of the variation in price *levels* is between retailers, rather than between stores within a retailer.

Figure 2.1 supports this decision. These histograms depict the degree of synchronization of price changes within different units of analysis. In Panel (a) of Figure 2.1, the X-axis represents the fraction of UPC-store combinations within a UPC-retailer-market that change their price during a given month. They are conditioned on at least one store changing their price. Panel (a) suggests that within a market, either all the stores of a given retailer change their price simultaneously (with a frequency of 5.2%) or that very few stores change their price. In only a small fraction of cases, does a relatively large portion of stores change their price while simultaneously a large fraction of stores does not change their price.

Panel (b) shows the fraction of price changes of UPC-store combinations within a UPC-retailer at the national level. It shows that the degree of synchronization of price changes is much lower at the national level. This is mostly easily seen by the fact that the fraction of cases where all stores simultaneously change their price drops by almost half to 2.7%. There seems to be considerable variation in price adjustment across markets within retailers. Panel (c) shows the fraction of stores for each product across retailers that are changing at the same time. If we look at the fraction of UPC-store combinations that change price within a UPC without considering variation in retailers, the mass of stores at unity all but disappears.

The evidence from Figure 2.1 suggests that much of the decision making for price adjustment is done at the UPC-retailer-market level. Therefore, for the main empirical results in this paper, we consider the UPC-retailer-market combination to be the unit of analysis. Aggregation to UPC-retailer-markets from UPC-stores removes some concern about measurement error at the expense of some variation. However, we include variation across markets, as we find considerable variation across markets in contrast to DellaVigna and Gentzkow (2019) who find little for price levels. After aggregation we have 18 million observations of UPC-retailer-market-months, an average of 150 thousand observations a month.

In Table 2.1 we provide some summary statistics of our sample given the aggregation described above. The average frequency of adjustment in our sample is 6.7 percent. The average absolute size of price adjustment conditional on adjustment is 14.8 percent and the median adjustment size is 10.4 percent. These statistics are comparable to other studies using retail scanner data such as Coibion et al. (2015) who find an average frequency of price change of 5.4 percent and absolute size of change of approximately 12 percent. The average revenue of a product in our sample is 1,230.85 dollars, with revenue ranging from 2.12 dollars for the lowest revenue products (1st percentile) to 16,863.32 dollars for the highest revenue products (99th percentile) per product retailer month.

In Table 2.2 we report some statistics on the number of products and stores per retailer-market. We have between 52 (10th percentile) and 868 (90th percentile) products per retailer-market suggesting a wide range of types of retailers, from small mom-and-pop types to large box store chains. Retailers have between 2 and 108 stores in each market. This is driven both by the size of the market (New York City versus Bangor, Maine), and the penetration of a given retailer in each market.

2.3.2 Empirical Results

We first test the relationship that product revenue has with both the probability and size of price changes. These relationships correspond to equations (2.6) and (2.7) of the previous section. Figure 2.2 summarizes our main findings. Panel (a) depicts the relationship between revenue and the probability of price adjustment in our sample. We compute the average monthly revenue of each product and group them into percentile bins by their revenue. We then compute the average probability of price adjustment and the average log revenue within each bin and plot this relationship. Panel (a) clearly shows a strong positive relationship between revenue and the probability of price adjustment. For example, a product in the tenth percentile of average revenue has a probability of adjustment of less then 1 percent, while a product at the ninetieth percentile has a probability of adjustment close to 15 percent per month.

Panel (b) depicts the relationship between revenue and the absolute size of price adjustment. It shows the average absolute size of adjustment and the average log revenue for each percentile bin. The figure shows a clear negative relationship between revenue and size of adjustment. The average size of adjustment for a product in the tenth percentile of average revenue is approximately 18 percent, while the average size of adjustment for a product at the ninetieth percentile is approximately 11 percent.

These figures report the averages of pricing behavior conditional on revenue, comparing across time as well as retailers, product categories, and markets. Although this simple exercise illustrates a very strong relationship, we proceed to test the robustness of the relationship controlling for various factors. We show in the next section that the relationships remain strong even as we add controls to mitigate potential concerns.

2.3.2.1 Revenue And Probability Of Price Adjustment

The variable adj_{ijmt} represents the observed revenue-weighted price adjustment for each UPC-retailer-market. This variable is the fraction of the revenue in stores that a price change is observed over the total revenue, for a given UPC i, of retailer j, in market m, during month t. Because of a high degree of correlation between price changes across stores for a given retailer this variable is often near one or zero. We estimate the relationship between this variable and lagged log revenue using the regression equation,

$$adj_{ijmt} = \alpha + \beta logrev_{ijmt-1} + \epsilon_{ijmt} \tag{2.17}$$

where $logrev_{ijmt-1}$ is the log revenue of UPC i, of retailer j, in market m, during month $t-1$.[15] Because price changes in a given month can directly affect revenue in that month, we use lagged rather than current revenue.[16] Depending on the specification, we include a number of fixed effects to address various concerns. Finally,

[15]Because we are concerned about changes in regular price, there may be some concern about how to treat revenue in weeks the product is on sale. Throughout the paper we use the average weekly revenue of a product in a given month, and multiply that number by four weeks to compute the monthly revenue. Alternatively, we have also tried using the average of weekly revenue of a product in weeks when the product is not on sale multiplied by four weeks for monthly revenue and found similar results (not reported).

[16]Regression with current log revenue give similar results (not reported).

we include a instrumental variables regression specification. Standard errors in all specifications are clustered on month, retailer and UPC separately, in order to alleviate concerns about correlation in consumer preferences within localities or products, retailer policy, UPC characteristics, and macroeconomic shocks.

We report the results in Table 2.3. These results confirm our earlier findings in Figure 2.2. Column (1) includes the month fixed effect to mitigate concerns about spurious correlations with long-term trends such as inflation and growth. Additionally, this should mitigate the effects of product entry and exit. In column (2), we add market, retailer, and UPC fixed effects separately to rule out the possibility that the relationship is driven by these differences. Column (3) includes UPC-retailer-market fixed effects (these are fixed effects at the product level as we have defined them). This eliminates the cross-sectional variation across products, and ensures the relationship is driven by variation across time. The remaining variation is across time for the same product, further alleviating concerns about unobserved factors driving the relationship between price adjustment and product revenue.

The various fixed effects alleviate concerns that unobserved factors may affect price adjustment and product revenue simultaneously. For example, several papers, including Bhattarai and Schoenle (2014), have documented that firms that sell more products are more likely to change the prices of each product. Then, because firms with more products may be more likely to have products with higher average revenue, one may worry that multi-product firms, not revenue, is actually driving our results. However, by removing variation at both the UPC and retailer level with fixed effects, we control for the extra returns to scope that multi-product firms experience in changing several prices at once. Our findings are complementary but separate.

In Column (4), we instrument $logrev_{ijmt-1}$ using the log of the total revenue for UPC i in period $t-1$, summing across all retailers in market m except for retailer j. We believe this instrument contains information regarding local demand that only affects price setting behavior through its effect on product revenue. Our preferred interpretation is that the revenue of UPC i in other retailers of the same market reflect the local change in the underlying preferences for UPC i. For example, this interpretation is consistent with standard monopolistic competition models with constant elasticity of substitution consumption aggregators and idiosyncratic preference shocks.

The coefficient on log revenue β is positive across all of our specifications. Additionally the coefficient is statistically significant at the 1% level for all specifications and also large economically. The coefficient of 0.0139 in column (1) suggests that a 10% increase in revenue increases price adjustment by 0.14 percentage points, which is approximately 2% of the average frequency of price adjustment in our sample. The coefficient remains quite stable across specifications, even as we include various fixed effects. The difference between the highest revenue goods (99th percentile) and lowest revenue goods (1st percentile) in our sample is approximately 9 log units, implying that the probability of a price change for the highest revenue products is about 12.5 percentage points higher for than products with the lowest revenue. In column (4) the first stage has an F-stat of 186.0 suggesting that our instrument is highly relevant. The instrumental variable specification, which includes the UPC-retailer-market fixed effects, has a very similar coefficient to that in column (1) but wider confidence intervals.

We also consider an alternative specification, in which we construct a binary variable D_{ijmt} that takes the value of one if the revenue-weighted percentage of prices that changed for UPC i, in retailer j, in market m, in month t, is greater than 17.6%.[17] This is a linear probability model with the positive outcome defined as a coordinated price change. This allows us to interpret the coefficient on lagged log revenue as the marginal effect of increasing log revenue on the probability of adjustment. We regress,

$$D_{ijmt} = \alpha + \beta logrev_{ijmt-1} + \epsilon_{ijmt}. \tag{2.18}$$

As before, we include specifications with month, market, retailer, UPC, and UPC-retailer-market fixed effects. We also include the instrumental variables specification using, as before, the log of the total revenue of the UPC in all other retailers of that market. The results are reported in Table 2.4.

The coefficient on log revenue β is positive across all specifications. The coefficient of 0.0236 in column (1) suggests that a 10% increase in revenue increases the probability of price adjustment by 0.24 percentage points, which is approximately 4% of the average probability of price adjustment. The coefficient, again, remains quite stable across specifications. The results are statistically significant at the 1% level for all specifications and again large economically. The implied difference in the probability of price change between the highest and lowest revenue products is

[17]We choose a cutoff value of 17.6% of revenue because it is the median percentage of revenue from stores that change, conditional on at least one store changing price in that market for a retailer.

approximately 21 percentage points.

2.3.2.2 Revenue And Size Of Price Adjustment

We also test for the relationship between revenue and the absolute size of price adjustment conditional on price adjustment. We construct the revenue-weighted absolute size of price adjustment variable $|\Delta p_{ijmt}|$ as follows. We first compute the changes in regular price week to week in each store for each UPC i, of retailer j, in market m, during month t. We keep changes larger than 1%. Then, we weight by each store's share of revenue among stores in a given retailer with observed price changes during the given month, and average the regular price changes in percentage terms.[18] We estimate,

$$|\Delta p_{ijt}| = \alpha_t + \beta logrev_{ijt-1} + \epsilon_{ijt}. \tag{2.19}$$

The coefficient β represents the expected increase in the size of adjustment given an increase in log revenue. As before, we cluster on month, retailer, and UPC. Additionally, we add specifications that include market, retailer, and UPC fixed effects separately. We include a specification that has a UPC-retailer-market fixed effect, which removes all variation between products that does not differ across time. Finally, we include the instrumental variables specification using the log of the total revenue of the UPC in all other retailers of that market as an instrument.

Table 2.5 shows the results. We find that the relationship between the size of price

[18] If a store changed regular price twice in a month each observation counts towards the average.

adjustment and revenue is negative and statistically significant across all specifications. From column (1), a coefficient of -0.0106 indicates that the average absolute size of price change will decrease by 0.11 percentage points when revenue increases by 10%. This is approximately 1.2% of the average size of adjustment in our sample. The implied difference in the average size of adjustment between the highest and lowest revenue products is approximately 10 percentage points.

In Table 2.5, the coefficient on log revenue decreases across specifications as we include more fixed effects. We believe that this is due to attenuation bias from measurement error. The R-squared increases from 0.018 in the first column to 0.458 in the third column, as the absolute size of the coefficient decreases from -0.0106 to -0.0044. This suggests that the fixed effects soak up much of the variation in the dependent variable as we add each one to the regression. As long as the measurement error is uncorrelated noise, its variance is less affected by the fixed effects than the true variation in revenue.[19] Our instrumental variable specification should alleviate classical measurement problems, which appears to be borne out by our results.

Nevertheless, the sign and the statistical significance of the results are stable

[19]This effect appears to be especially relevant for regression equation (2.19) compared to regression equations (2.17) and (2.18) due to the differences in the group sizes we use in estimation. While we utilize all observations of revenue and price to estimate the probability of adjustment, we only use observations for which there are price changes to estimate equation (2.19). Once we control for UPC-retailer-market fixed effects, we are left only with the within product variation in the size of price changes. Price adjustment is relatively infrequent and we are left with little variation in the independent variable to accurately estimate column (3) of Table 2.19. For example, imagine a product for which we have 5 years of monthly observations, and the price of the product adjusts 6 times during that span. Then for regression equation (2.17) we would have 60 observations, whereas for equation (2.19) we would only have 6 observations. As the result in column (1) is the least susceptible to attenuation bias and most consistent with Figure 2.2b, we use this estimate to calibrate our model in Section 2.4.

across all specifications, strongly suggesting a robust negative relationship which is consistent with our theoretical predictions. Considering the results of Tables 2.3, 2.4, and 2.5, we conclude that there is a fundamental relationship between revenue and price adjustment that cannot be attributed to systematic differences across UPCs, retailers, markets or any other time invariant product characteristics. We also believe that it is unlikely that an unobserved variable would cause fluctuations in product revenue over time, while simultaneously increasing the probability of price change and decreasing the size of price changes in relation to revenue. Finally, we believe that our instrumental variable specifications show that changes to price setting behavior is indeed induced by the movements in the revenue of the product and not by other factors.

Estimation equations (2.17), (2.18), and (2.19) are the empirical counterparts to a weighted sum across products of equations (2.6) and (2.7). The signs of these theoretical derivations do not change with product level characteristics, and thus a weighted average of these expressions will be equal to the sign of the individual equations. We conclude that in the context of the theory developed in Section 2.2 that $k < 1$ and that revenue is non-neutral.

2.3.2.3 Revenue And Monetary Policy Transmission

In this section, we estimate the responsive of prices to a monetary policy shock. Our theoretical results in Section 2.2.2 and the empirical results in the previous section suggest that the responsiveness of prices will be larger for products with higher revenue. We use monetary shocks constructed from high frequency data of current month federal fund futures on Federal Open Market Committee (FOMC) announcement dates. We use the federal fund surprises constructed by Paul (2019) from 2006-2015,[20] which we augment to include shocks from unscheduled meetings from January 2008 to December 2009 from Gorodnichenko and Weber (2012).[21]

Using local projections on the panel of price changes, we estimate the impulse response of prices to a monetary policy shock by each quantile of revenue. We group products into revenue quantiles by sorting products by revenue within each market, and assign the lowest 20% of products into quantile 1, the next 20% into quantile 2 and so forth. We do this within each market month. We estimate the following equation for 18 periods:[22]

$$\Delta lnp_{q,t} = \alpha_q + \beta_{q,h} * \Delta m_{t-h} + \epsilon_{q,t-h}. \tag{2.20}$$

We construct cumulative responses by summing across coefficients up to a given horizon.[23] Figure 2.3 shows the impulse response of price levels for each quantile of revenue in response to an unexpected increase of 100 basis points in the federal funds

[20]Paul (2019) documents that an unexpected increase in the federal funds rate leads to a fall in aggregate prices and output as should be expected.

[21]We also report results using shocks without the unscheduled meetings in Appendix B. The results are similar but with larger confidence intervals.

[22]Our sample of price changes runs from January 2006 to December 2015. For the monetary shocks we use information as far back as July 2004. This ensures that the price response variable are all from a common time period for all horizons, while simultaneously utilizing all observations regarding price responses.

[23]The individual coefficients $\beta_{q,h}$ are reported in Appendix B.

rate. Each panel shows the price response of products in each quantile, and the one standard deviation and 90% confidence intervals by order of quantile.[24] The prices of products in the lowest revenue quantile respond the least, and show very little adjustment to a monetary shock. The prices of the highest revenue quantile respond the most. The magnitude of the cumulative response of prices following a monetary shock increases with each revenue quantile at horizons over a year. The impulse response functions are significantly different from zero for all quantiles at such horizons. In addition, the 90% confidence intervals of the lowest quantile products and that of the highest quantile products do not overlap at various points past the 12 month mark, suggesting that the difference is statistically significant. We perform a Welch's t-test of the null hypothesis that the (cumulative) impulse response for the fifth quantile is not greater than the response for the first quantile after 12 months, based on simulated standard errors. A single sided test rejects the null hypothesis with a p-value of less than 1%.

Our results suggest that the response of prices to a monetary shock is increasing in revenue. The cumulative response of the point estimates suggest that the response of prices of products in the lowest quantile of revenue is 19% of the response of prices for products in the highest quantile of revenue over 12 months and 26% over 18 months.

Our empirical results support our theoretical results in Section 2.2. They demonstrate the importance of product revenue for not only price setting behavior at the

[24] We show one standard deviation and 90% confidence intervals based on a Monte Carlo simulations where we draw a coefficient at each horizon from its limiting distribution. We use 2000 separate draws for each confidence interval.

micro level, but also for the real effect of monetary policy. In Section 2.4, we explore the aggregate implications of our theoretical and empirical findings. However, before exploring the aggregate implications, we first document the business cycle movements of the cross-sectional distribution of revenue across products, as business cycle movements in the revenue distribution can potentially interact with price responsiveness in an meaningful way.

2.3.2.4 Revenue Distribution And Unemployment

To study the interaction between price setting decisions and the revenue distribution, we document the movements of the revenue distribution across the business cycle. Our sample period is 10 years, which is relatively short for analyzing business cycle movements. However, we leverage the fact that we have observations in many markets and exploit variation in regional unemployment. For this exercise we expand our sample to include 190 product categories. We expand the sample at this point for a few reasons. The fact that our unit of observation is now a moment of the cross-sectional revenue distribution in each time period (rather than product) greatly decreases the computational burden and allows us to handle more product categories. Expanding the sample also gives us greater coverage of products and increased statistical power. However, our results remain unchanged when we use the 30 product categories as before (reported in Table B.7 of Appendix B).

To document the relationship between the regional unemployment rate and various moments of the log revenue distribution, we estimate,

$$Y_{cmt} = \alpha_t + \delta_c + \gamma_m + \beta \cdot UR_{mt} + \epsilon_{cmt} \tag{2.21}$$

where Y_{cmt} is a statistic for the distribution of revenue for product category c in market m in month t. UR_{mt} is the unemployment rate for the region m.[25] α_t is the month fixed effect, δ_c is the product category fixed effect, and γ_m is the market fixed effect. The statistics we use for the left-hand-side variable Y_{cmt} include the mean, the median, the standard deviation, and the difference in log revenue between a product at the 90th percentile in revenue and 10th percentile in revenue (the spread).

We include month fixed effects for several reasons. First, they remove the secular and nominal trends from the data, addressing concerns about spurious long-run trends driving our results. Second, the inclusion of month fixed effects suggests that the relationship between unemployment and revenue is driven by demand as discussed by Coibion et al. (2015). Because most goods are produced outside the local market, aggregate productivity shocks are external to the market, implying that changes in revenue and unemployment are correlated mostly through local demand and local supply conditions. The standard errors are clustered by market, product category, and month, to address concerns about temporal and spatial correlations.

Table 2.6 shows the results. We find that not only do the mean and median of the distribution of revenue decrease in recessions, as to be expected, but that both the

[25]The regional unemployment rate UR_{mt} is computed as the population weighted unemployment rate of the counties that constitute market m. The unemployment rates by county are obtained from the American Community Survey.

standard deviation and the spread between the 90th and 10th percentile goods falls as well. The results show that a 1% increase in regional unemployment corresponds approximately to a 1.2% decrease in mean revenue, a 1.3% decrease in the median revenue, a 0.40% decrease in the standard deviation and a 1.0% decrease in the revenue spread.

Not only the level, but also the variance of the revenue distribution is meaningful for monetary policy because the response of aggregate prices to a monetary shock increases with the variance of revenue distribution. As the variance increases, the price of high revenue products that constitute a proportionately larger fraction of aggregate price become more responsive to monetary shocks. The price of low revenue products become less responsive, but these only constitute a small and decreasing proportional of aggregate price.

While we are focused on documenting the behavior of the revenue distribution and do not investigate further into the reasons behind these patterns, recent studies of consumer shopping behavior over the business cycle provide potential channels through which this may occur. For example, Coibion et al. (2015) find that households reallocate consumption expenditures toward low-price retailers when local economic conditions deteriorate. Jaimovich et al. (2017) find that people traded down in the quality of goods and services they consumed during the Great Recession. Nevo and Wong (2017) document extensive substitution behavior by consumers over the business cycle. They find that households increase coupon usage, increase purchases of goods on sale, buy larger sized products, buy generic products, and substitute purchases toward big box (discount) stores during recessions. Any one or a combination of these consumer substitution patterns could potentially generate the movements in the revenue distribution that we document.

2.4 Aggregate Implications

Our results in Sections 2.2 and 2.3 suggest that revenue is non-neutral and has important implications for the real effect of monetary policy. In this section, we use a quantitative dynamic model to demonstrate our theoretical predictions in a fully general equilibrium setting. Then, we utilize the model to show that the distribution of revenue has a meaningful effect on monetary policy transmission.

2.4.1 Quantitative Model

We build a quantitative model that matches both the pricing moments found in the microdata and business cycle variations in the revenue distribution. We augment a standard menu cost model similar to those found in Golosov and Lucas (2007) and Midrigan (2011) to match the shifts in the revenue distribution across the business cycle. We use this model to demonstrate the effect of revenue variation for price setting behavior and monetary policy transmission. In addition, we quantify the degree of state-dependence of monetary transmission implied by our mechanism.

Households

Households maximize discounted expected utility,

$$\max E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \{\phi_{t+\tau} \frac{(C_{t+\tau})^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} - \frac{N_{t+\tau}^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}}\} \tag{2.22}$$

subject to the budget constraint,

$$P_t C_t + B_t = R_{t-1} B_{t-1} + W_t N_t + \Pi_t.$$

C_t is the household consumption of the composite good, N_t is total labor supply, B_t is one-period nominal bonds, P_t is the aggregate price level, R_t is the nominal rate of return, W_t is nominal wage, and Π_t is the firm profits that are transferred to the households. ϕ_t is an aggregate preference shock that represents a shock to the discount rate and affects the intertemporal substitution of households.

Households consume a continuum of a variety of products indexed by i. The composite good C_t is a Dixit-Stiglitz index of these products,

$$C_t = \Big(\int_0^1 \big(\iota_{it} c_{it}\big)^{\frac{\epsilon-1}{\epsilon}} di \Big)^{\frac{\epsilon}{\epsilon-1}} \tag{2.23}$$

where ι_{it} is the idiosyncratic preference for product i and ϵ is the elasticity of substitution across goods. Households choose to consume variety c_{it} to maximize C_t subject to the constraint,

$$\int_0^1 q_{it}^{-1} p_{it} c_{it} = P_t C_t$$

where p_{it} is the price of product i. The household's subproblem of variety choice is standard except for q_{it}. In this model q_{it} serves as an exogenous demand shifter that is needed to match the documented changes in the revenue distribution across the business cycle. We treat q_{it} as exogenous in order to focus on the firm's decision process and remain amenable to different household processes that may generate the shifts in demand. One possible interpretation of q_{it} is as the cost of shopping effort (see Coibion et al., 2015). Another interpretation would treat q_{it} as the household's valuation of product quality, defined as a function of the product's idiosyncratic components (z_{it}, ι_{it}), where z_{it} is the idiosyncratic productivity of the producer. This interpretation is in line with the findings of Jaimovich et al. (2017).[26]

We model q_{it} as depending on the aggregate state of the economy as well as the idiosyncratic characteristics of the product.

$$q_{it} = q(\tilde{q}(z_{it}, \iota_{it}), \phi_t)$$

To be consistent with the empirical findings in Section 2.3.2.4 we impose the condition that,

$$\frac{\partial^2 lnq_t}{\partial ln\tilde{q}_t \partial ln\phi_t} > 0$$

With a shopping cost interpretation, this condition means that in recessions the opportunity cost of time falls, and it becomes less costly to buy products that households usually purchase infrequently. A product quality interpretation would imply that household sensitivity to quality differences decreases in recessions.

[26] To interpret as valuation of product quality it may be more intuitive to specify q_{it} as a part of the composite good index $C_t = (\int (q_{it}\iota_{it}c_{it})^{\frac{\epsilon-1}{\epsilon}} di)^{\frac{\epsilon}{\epsilon-1}}$ which gives almost identical results.

The inclusion of idiosyncratic preferences ι_{it} is necessary because the revenue distribution is an important determinant of output fluctuations in our setting. Studies such as Burnstein and Hellwig (2007) and Kumar and Zhang (2016) find that demand shocks constitute a large fraction of the idiosyncratic shocks that firms face, and ignoring this component may lead to an understatement of revenue dispersion. In the calibration of this model, we find that this is true in our sample as well.

The demand curve for good c_{it} then follows,

$$c_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\epsilon} q_{it}^{\epsilon} \iota_{it}^{\epsilon-1} C_t \tag{2.24}$$

and the expression for the aggregate price index can be derived as

$$P_t = \left\{ \int_0^1 \left(\frac{p_{it}}{q_{it}\iota_{it}}\right)^{1-\epsilon} di \right\}^{\frac{1}{1-\epsilon}}. \tag{2.25}$$

Aggregate Shocks

Following much of the literature on menu cost models, we assume that the monetary authority conducts monetary policy by targeting a path of nominal GDP

$$lnM_t = lnM_{t-1} + \nu_t^m \tag{2.26}$$

where $M_t = P_t Y_t$ is nominal GDP. Innovations ν_t^m follow the normal distribution

$N(0, \sigma_m^2)$. The aggregate preference parameter ϕ_t follows,

$$ln\phi_t = \rho_\phi ln\phi_{t-1} + \nu_t^\phi. \tag{2.27}$$

and ν_t^ϕ follows $N(0, \sigma_\phi^2)$.

Firms

Firms produce a differentiated product y_{it} with linear production technology

$$y_{it} = z_{it} n_{it}$$

where z_{it} is firm i's idiosyncratic productivity and n_{it} is labor demand. The firm's current period real profit is,

$$\pi_{it} = \left(\frac{p_{it}}{P_t} - \frac{W_t}{z_{it} P_t}\right) y_{it}$$

where the demand for y_{it} is given by equation (2.24).

Now consider the firm's dynamic problem. Henceforth, for notational simplicity we omit the subscript i except when explicitly necessary. It is more convenient to express the firm's dynamic problem in terms of real markup $\mu_t = \frac{p_t z_t}{W_t}$. Substituting in equation (2.24) for y_t, the firm's current period profit is

$$\pi_t = (\mu_t - 1)\mu_t^{-\epsilon} q_t^\epsilon (z_t \iota_t)^{\epsilon-1} Y_t \left(\frac{W_t}{P_t}\right)^{1-\epsilon}.$$

Idiosyncratic productivity follows the process

$$lnz_t = lnz_{t-1} + \nu_t^z$$

where ν_t^z is a shock to productivity. The shock ν_t^z follows a Poisson process,

$$\nu_t^z \sim \left\{ \begin{array}{ll} 0 & : \text{with probability } \theta_z \\ N(0, \sigma_z^2) & : \text{with probability } 1 - \theta_z \end{array} \right\}$$

and idiosyncratic demand evolves according to

$$ln\iota_t = ln\iota_{t-1} + \nu_t^\iota$$

where ν_t^ι follows the normal distribution $N(0, \sigma_\iota^2)$. We assume that log productivity and log demand follow a random walk, which allows us to define the idiosyncratic state of a firm jointly as $\omega_t = z_t \iota_t$. This reduces the number of state variables and decreases the computational burden of solving this model numerically. The idiosyncratic state ω_t then follows

$$ln\omega_t = ln\omega_{t-1} + \nu_t^z + \nu_t^\iota$$

Since this variable follows a random walk, we include a probability of firm exit to keep the distribution of firms stationary. We assume that firms exit with probability α. When a firm exits, it is replaced by a new firm with $z_t = \iota_t = \omega_t = 1$. We now write the firm's dynamic problem, where each period it must pay a small menu cost

b_t to change its price as,

$$
\begin{aligned}
&V(\mu_t, \omega_t; Y_t, \phi_t) \\
&= \max \Bigg\{ \pi(\mu_t, \omega_t, Y_t, \phi_t) + (1-\alpha)\beta E_t \Lambda_{t+1} V\Big(\mu_{t+1}, \omega_{t+1}; Y_{t+1}, \phi_{t+1}\Big), \\
&\quad \max_{\tilde{\mu}} \Big\{ \pi(\tilde{\mu}, \omega_t, Y_t, \phi_t) + (1-\alpha)\beta E_t \Lambda_{t+1} V\Big(\mu_{t+1}, \omega_{t+1}; Y_{t+1}, \phi_{t+1}\Big)\Big\} - b_t \Bigg\}
\end{aligned}
$$

where Λ_{t+1} is the stochastic discount factor.

As in Section 2.2 we assume that the menu cost b_t is equal to $\bar{b} \cdot (rev^*)^k$. Thus b_t has the form,

$$b_t = \bar{b} \cdot \Big((\mu^*)^{1-\epsilon} q_t^{\epsilon} \omega_t^{\epsilon-1} Y_t \big(\frac{W_t}{P_t}\big)^{1-\epsilon} \Big)^k \tag{2.28}$$

where μ^* is the desired optimal markup of the firm. We also assume that with a small probability χ the menu cost b_t is equal to zero. This introduces some time-dependence in price setting behavior and is often thought of as a reduced form mechanism of complicated processes that generate small changes to menu costs such as, for example, the existence of multi-product firms.

In what follows, we compare the baseline case in which revenue variation matters for the price setting problem ($k < 1$) with the revenue neutral case ($k = 1$). We demonstrate that the empirical relationship between revenue and price setting documented in Section 2.3 is inconsistent with the revenue neutral case. Furthermore, we demonstrate the aggregate implications of accounting for revenue variation in the price setting problem with regard to the real effect of monetary policy.

We use log linear approximations of the relationship between labor supply and output to allow convenient aggregation as in Nakamura and Steinsson (2010). We use the Krusell and Smith (1998) algorithm to solve the model numerically. We assume that firms perceive the evolution of the price level $\frac{P_{t+1}}{P_t}$ as a function of variables,

$$ln\Big(\frac{P_{t+1}}{P_t}\Big) = \Gamma(lnY_t, ln\phi_t, \nu^{\phi}_{t+1}, \nu^{m}_{t+1}).$$

The function $\Gamma(\cdot)$ is a linear function of the variables, their squares, and the interaction terms between the shocks and the aggregate state variables. The resulting R^2 of the regression of the perceived evolution on the actual evolution is in excess of 99%.

2.4.2 Calibration And Results

Following our empirical results, we set the time unit of the model to a month. The time discount factor β is set to an annual value of 0.96. Following much of the menu cost literature, we set the intertemporal elasticity of substitution γ equal to 1 and the inverse Frisch elasticity $\frac{1}{\eta}$ to zero to facilitate computation. We calibrate the elasticity of demand to $\epsilon = 3$, which is in line with the median elasticities estimated in Nevo (2001) and Broda and Weinstein (2006).

The standard deviation for nominal GDP σ_m is calibrated to be 0.52 percent, which is the standard deviation of the HP-filtered nominal GDP between 1947 and 2019. The persistance (ρ_ϕ) and the variance (σ_ϕ) of the preference parameter ϕ_t is calibrated such that the persistence and variance of real GDP in the model is equal to 0.946 and 0.48 percent, matching that of the HP-filtered real GDP series from 1947 to 2019.

For the baseline case with revenue variation ($k < 1$), the parameters governing the productivity process, the demand process, the rate of product exit, and the intercept of the menu cost $(\theta_z, \sigma_z, \sigma_\iota, \alpha, \bar{b})$ are jointly calibrated to match the average frequency of adjustment, the median absolute size of adjustment, the variance of log revenue, the strength of the relationship between the probability of adjustment and revenue, and the strength of the relationship between the absolute size of adjustment and revenue. We target an average frequency of adjustment of 6.7% and a median absolute size of adjustment of 10.4% to match the moments from our sample.[27] We target the variance of revenue to be 1.30 in steady state which is what we find in our dataset. We target for the probability of adjustment to increase by 0.14 percentage points, and the absolute size of adjustment to decrease by 0.11 percentage points, in response to a 10% increase in revenue. This reflects the results from column (1) of Table 2.3 and Table 2.5 respectively.

We calibrate the frequency of productivity shocks $1 - \theta_z$ to be 14.6% and the standard deviation of the shock σ_z to be 8.5%. The standard deviation of the demand shock σ_ι is set to 15.2%, and the rate of product exit is set to 7.5%. The size of the menu cost b is 0.022 which implies that the total cost of changing prices amounts to 0.3% of the steady state revenue. This is smaller than the value of 0.7% of revenue found by Levy et al. (1997).

The parameters governing the degree to which menu cost increases with revenue k and the probability of zero menu cost χ are set to 0.301 and 1.27% respectively.

[27] We calibrate to the median absolute size of adjustment instead of the mean to alleviate the effects of outliers, as is common in the literature. In our model, the mean and the median size of adjustment are close in value whereas in the data there is a larger difference. This suggests that the tails of the distribution of the size of price changes are thicker than implied by the shock processes in our model.

We estimate these parameters from our sample using a parametric model based on our results in Section 2.2 and comparable to the current model. A full discussion of how we estimate these parameters can be found in Appendix B

We adopt the following functional form for lnq_t in order to match the changes in the revenue distribution over the business cycle,

$$lnq_t = \psi_0 \cdot ((1+\psi_1) \cdot \min(ln\omega_t, 0) + (1-\psi_1) \cdot \max(ln\omega_t, 0) + \psi_2) \cdot ln\phi_t.$$

Parameters (ψ_0, ψ_1, ψ_2) are calibrated to match the change in the mean, the median, and the standard deviation of the log revenue distribution with the state of the economy as shown in Table 2.6.

For the revenue neutral case ($k = 1$), we choose to keep the same parameters as the baseline model with the exception of the menu cost parameter $\bar{b}$, which we calibrate to match the frequency of price adjustment in the data. We believe that this approach allows for the most direct comparison between the model economies, and worry that recalibrating all the parameters would raise the issue of comparability across models. Although we have not recalibrated the parameters, the revenue neutral version of the model also does a relatively good job of matching the data moments.[28] The results are shown in Tables 2.7 and 2.8.

Figure 2.4 compares the steady state relationship between price setting behavior and revenue of the two model economies. Panels (a) and (b) show the relationship between price setting and revenue in the baseline economy. Panel (a) depicts the

[28] We have experimented with recalibrating all parameters to match the target moments and all our results remain qualitatively the same and quantitatively similar (unreported).

relationship between the probability of price adjustment and log revenue. We group each product-month observation by revenue into percentile bins and compute the average revenue and the probability of adjustment for each bin. Then, we compute the log deviation of this revenue from the mean revenue and plot, for each percentile bin, the log deviation from mean revenue and mean probability of adjustment. The solid line represents the calibration target, with a slope of 0.014 between log revenue and probability of adjustment. Panel (b) of Figure 2.4 shows the relationship between the absolute size of price adjustment and revenue. As in Panel (a), we plot the log deviation from mean revenue and the mean size of adjustment for each percentile bin. The solid line represents the calibration target, with a slope of -0.011 between log revenue and size of adjustment.

Panels (a) and (b) show quite clearly that the relationship between revenue and price setting in the baseline economy closely resembles the relationship in the data. The relationship is robust throughout the support of revenue and is consistent in magnitude. The relationship between probability and size of adjustment with product revenue shown in Panels (a) and (b), closely resemble the same relationship found in the data, shown in Figure 2.2.

Panels (c) and (d) show the relationship between price setting and revenue in the revenue neutral economy. The contrast between the relationship in the revenue neutral economy to the baseline economy is stark. There is no discernible relationship between probability and size of adjustment with product revenue.

In order to measure the impact of monetary policy in our model, we estimate the impulse response of output using data generated via simulation. We generate

30,000 periods for estimation and estimate impulse responses using local projection methods. Since we generate the monetary shock, we treat it as an exogenous shock for the purposes of estimation. The estimation results are then used to project the impact of a one standard deviation shock to nominal GDP. All confidence intervals around the impulse responses are based on Newey-West standard errors and have 95% asymptotic significance.[29]

Figure 2.5 shows the impulse response functions of the revenue weighted average log price change in response to a monetary shock by quantile of revenue.[30] The gray line shows the baseline economy and the dashed red line represents the revenue neutral economy. The price response is similar between the two economies for the lower revenue quantiles but for quantiles 4 and 5 the price response is much greater for the baseline economy.

In the baseline economy, the model predicts that the response of prices in the first quantile is 50% of that of the highest quantile products during the initial period, and 62% of the cumulative response over the first quarter. For comparison, our empirical results in Section 2.3.2.3 show that the price response of the lowest quantile amounts

[29]We use local projections implemented by the *lpirfs* package available in R. For the linear local projections we treat the nominal gdp innovations as exogenous shocks. We fix the lag length of the endogenous variables at 1. For the non-linear local projections we use a binary variable to characterize the states, namely a dummy variable for whether the real gdp is in the 25th or below percentile of the simulations. This is a simpler version of the estimator from Ramey and Zubairy (2018) as the state is treated as binary not continuous. For all regressions we use Newey-West standard errors that allow a lag length of up to 10.

[30]The log price change used in Figure 2.5 is the revenue weighted average of price change of individual firms, which is directly analogous to our treatment in the empirical and theoretical analysis. However, they do not correspond exactly to the composite price index defined by equation (2.25). Therefore, our output response function and price response function do not necessarily add up to the monetary shock.

to 19% of the response of the highest quantile over 12 months and 26% over 18 months.

Figure 2.6 depicts the impulse response function of output to a unit monetary shock. The gray line depicts the response of output to monetary policy for the baseline economy ($k < 1$), and the dashed red line represents the response for the revenue neutral economy ($k = 1$). The shaded areas represent 95% deviation confidence intervals. The figure shows that the effect of monetary policy is considerably stronger for the revenue neutral case compared to the baseline calibration. The difference in the cumulative effect, measured as the percent difference of the area under the two impulse response functions, implies that real effect is 50.6% percent stronger for the neutral case. The fact that the price of high revenue products in the baseline economy is more responsive to monetary shocks drive the difference in the real effect of monetary policy between the two economies.

In Figure 2.7, we explore the implications of revenue variation for the state-dependence of monetary policy. Panel (a) depicts the impulse response for the baseline economy and Panel (b) depicts the impulse response for the revenue neutral economy. The blue line in Panels (a) and (b) represent the impulse response of output in the low output state, defined as output in the bottom quarter of simulated periods. The dashed green line represents the output response in the high output state, which includes all states not defined as a low output state. Panel (c) depicts the counter-cyclicality of monetary policy transmission. The gray line plots the degree of counter-cyclicality of output response in the baseline economy, by computing the difference in the output response in a high versus low output state as a fraction of the impulse response in a high output state. The dashed red line does the same for the revenue neutral economy.

The degree of counter-cyclicality in the real effect of monetary policy is larger for the baseline economy. In the baseline case, the cumulative output response is 14.9% larger in the low output state compared to the high output state. In the revenue neutral economy the cumulative effect is more similar, with the output response 6.3% larger in the low output state. The degree of counter-cyclicality induced by movements in the revenue distribution across the business cycle thus amounts to 8.6%.

Figures 2.5 through 2.7 illustrate the importance of accounting for revenue variation in price setting models. Under revenue non-neutrality, the responsiveness of prices to a monetary shock differs by as much as twice due to differences in revenue. This results in large heterogeneity in the effect of monetary policy across firms by revenue. Furthermore, the variance in the responsiveness causes the output response to monetary policy to be 50.6% smaller in the baseline economy compared to the revenue neutral economy. Finally, revenue variation also implies that monetary policy transmission is stronger during recessions compared to expansions. However, this effect is small due to the fact that the differences in revenue across the business cycle are much smaller than the variation of revenue across products.

2.4.3 Extension – Volatility Shocks

In this section we consider an extension of our model to include counter-cyclical volatility shocks.[31] We match the negative correlation between average frequency of adjustment and aggregate output that we observe in the data using volatility shocks similar to those in Vavra (2014).

We model the variance of the idiosyncratic productivity shocks z_t to increase as the economy worsens. Specifically, the standard deviation of firm-level idiosyncratic productivity shocks d_t follows,

$$logd_t = \rho_d logd_{t-1} + \nu_t^d \tag{2.29}$$

where $\nu_t^d \sim N(0, \sigma_d^2)$. Then, the idiosyncratic productivity follows the process,

$$lnz_t = lnz_{t-1} + d_{t-1}\nu_t^z$$

and ν_t^z follows the Poisson process,

$$\nu_t^z \sim \left\{ \begin{array}{ll} 0 & : \text{with probability } \theta_z \\ N(0, \sigma_z^2) & : \text{with probability } 1 - \theta_z \end{array} \right\}$$

as before.

[31] Vavra (2014) argues that counter-cyclical volatility shocks are needed to match the counter-cyclicality in the average frequency of price adjustment found in the his data. Bachman et al. (2019) find that heightened idiosyncratic volatility increases the probability of price change using German firm data.

Similar to Vavra (2014), we make the assumption that d_t is perfectly negatively correlated with the aggregate demand process ϕ_t to facilitate computation. In other words we impose that $\rho_\phi = \rho_d$ and $u_t^\phi = -u_t^d$, where $v_t^\phi = \sigma_\phi u_t$, $v_t^d = -\sigma_d u_t$, and $u_t \sim N(0,1)$. This allows us to reduce the state space in the computation of the model.

We calibrate the standard deviation of the idiosyncratic volatility shock to match the relationship between aggregate output and average frequency of adjustment over the business cycle in our sample.[32] The other parameters remain unchanged. Table 2.9 shows the business cycle moments of the extended model.

Figure 2.8 compares the impulse response function of output to a monetary policy shock between economies with different volatility shocks. The gray line shows the impulse response of our original model without the volatility shocks. The dashed red line shows the impulse response when the frequency-output coefficient equals -0.035, and the dashed blue line shows the impulse response when the coefficient is equal to -0.072. The response of output increases slightly with the inclusion of volatility shocks, but the difference is minimal.

Figure 2.9 shows the degree of counter-cyclicality – the difference in the output response between low and high output states – for different volatility shocks. The degree of counter-cyclicality in the output response decreases as the volatility shocks get larger, as originally argued by Vavra(2014). Figure 2.9 shows that with volatility

[32]We present our results regarding the correlation between the average frequency of price change and the business cycle in Appendix B. Our results also show a negative correlation between average frequency of price change and output. The magnitude of the relationship that we find in our data is similar in magnitude of that found in Vavra (2014).

shocks that match the data on the relationship between output and the average frequency of adjustment, the effect of the volatility shocks approximately cancel out the impact of revenue variation on monetary transmission over the business cycle.

We note that the degree of pro-cyclicality implied by the volatility shocks in our model is much smaller than what is suggested by Vavra (2014). We believe that the main difference is in the magnitude of the extensive margin. In Vavra's model, the extensive margin effect is very large, approximately twice as large as the intensive margin effect on average. Furthermore the difference in the extensive margin effect over the business cycle is almost as large as the intensive margin effect itself. We find that in our model the extensive margin effect is small and does not move much over the business cycle.

For example, even in the economy with the largest volatility shocks (-0.072), the revenue weighted frequency of change immediately following a monetary shock(i.e. the intensive margin effect) is equal to 13.1% in the low output state and 12.8% in the high state. The extensive margin effect, computed as the difference between the initial impulse response of the revenue weighted average log price change and the intensive margin effect, is equal to 15.6% in the low output state and 16.4% in the high output state. The size of the extensive margin effect and its differences across states is relatively small.

It is important to take into consideration that our calibration differs considerably from that of Vavra, who calibrates to moments constructed from a broader CPI database. In addition, our calibration explicitly targets revenue moments which the CPI database does not contain. These factors may contribute to the difference in the magnitude of the extensive margin effect. Nevertheless, our results to do suggest that the relative size of the extensive margin effect and its change over the business cycle should be examined more closely.

2.5 Conclusion

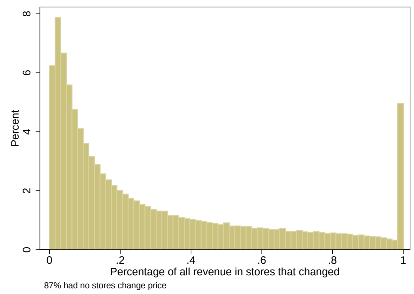
Accounting for variation in product revenue is crucial to understanding price setting behavior and monetary policy transmission. We find that in the data, the probability of price adjustment increases in product revenue, while the average size of price adjustment decreases in revenue. The responsiveness of prices to monetary policy shocks increases with revenue. These facts all indicate the non-neutrality of revenue.

The non-neutrality of revenue matters for the real effect of monetary policy. Using a calibrated menu cost model, we find that the implied non-neutrality based on pricing moments implies that price response can differ by as much as double across products with different levels of revenue. As a result, the cumulative output response to a monetary policy shock in a non-neutral economy is about half that of a revenue neutral economy. Revenue variation also introduces a counter-cyclical force in monetary policy transmission, which cancels out the pro-cyclical effects of counter-cyclical volatility shocks.

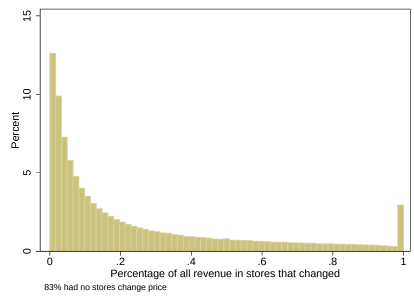
We uncover substantial heterogeneity in the effect of monetary policy across products with different revenues. This heterogeneity offers insight into the nature of menu costs and the monetary policy transmission mechanism. We believe understanding such heterogeneities can be beneficial in understanding the distributional consequences of monetary policy as well as for optimal policy design. In addition, we contend heterogeneity in the responsiveness of prices across products has important consequences for our understanding of monetary policy's aggregate real effects.

Our findings suggest that product revenue should be explicitly considered when studying price setting behavior and monetary policy. This may be most relevant in cases where the variance of revenue across similar products is substantial. In this paper, we document cross-sectional, aggregate, and business cycle implications. However, revenue variation may also be a key consideration in other settings, such the effect of monetary policy across different localities where the differences in the revenue distribution may be large.

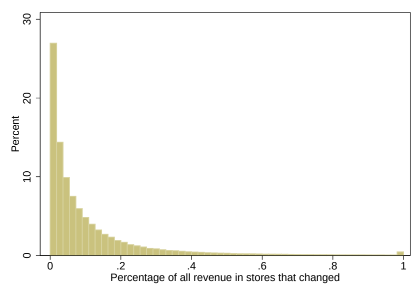
Finally, we show that the specific form of adjustment costs can have important consequences for both microeconomic and macroeconomic behavior. Our findings may be relevant to other settings such as investment dynamics and employment decisions where fixed adjustment costs play an important role. A careful exploration of the nature of the adjustment costs may be warranted.



(a) UPC-retailer-market



(b) UPC-retailer



(c) UPC

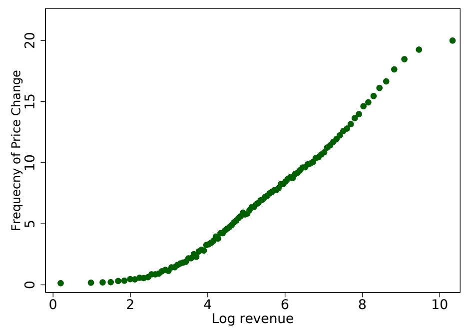
Figure 2.1: Histogram of synchronization of price adjustment
Note: We show the percentage of revenue from stores that adjusted price for each month and level of aggregation. Panel (a) shows the results for aggregation to the UPC-retailer-market, Panel (b) shows the results for aggregation to the UPC-retailer (national), and Panel (c) shows the results for aggregation to the UPC.

Table 2.1: Summary statistics

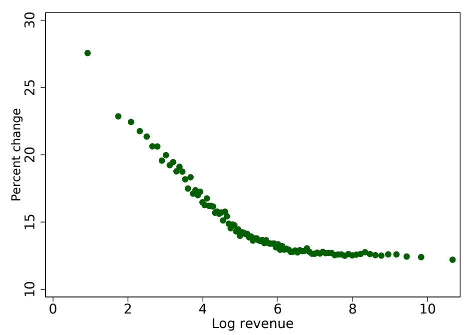
Statistic		Revenue	
Adjustment frequency	6.7%	1st percentile	$2.12
Average adjustment size	14.8%	10th percentile	$11.12
Median adjustment size	10.4%	50th percentile	$166.46
		90th percentile	$2,584.34
		99th percentile	$16,863.32
		Average revenue	$1,230.85

Table 2.2: Products and stores per retailer-market

	Number of Products	Number of Stores
10th Percentile	52	2
50th Percentile	308	18
90th Percentile	868	105
Average	405	18



Probability of adjustment



Size of adjustment

Figure 2.2: Product revenue and price setting

Note: We compute the revenue-weighted average probability and absolute size of price adjustment in each UPC-retailer-market-month. We take a simple average of this variable, grouped into percentile bins by order of revenue. We plot each percentile bin showing average log revenue on the X-axis and the average probability of adjustment or the average absolute size on the Y-axis. For a full discussion of the construction of the variables see Section 2.3.2.

Table 2.3: Probability of price adjustment

	(1)	(2)	(3)	(4)
log revenue	0.0139	0.0115	0.0108	0.0132
	(0.0003)	(0.0002)	(0.0003)	(0.0012)
Observations	18,252,975	18,252,975	18,252,975	14,644,079
R-squared	0.041	0.085	0.133	0.133
Month FE	Y	Y	Y	Y
Market FE	N	Y	-	-
Retailer FE	N	Y	-	-
UPC FE	N	Y	-	-
UPC-retailer-market FE	N	N	Y	Y
Instrumental variable	N	N	N	Y
1st Stage F-stat	-	-	-	186.00

Note: The dependent variable is the revenue-weighted fraction of price changes observed for a UPC-retailer-market each month. The independent variable of interest is the log of the total lagged revenue of a UPC-retailer-market each month. The instrumental variable is the log of the total lagged revenue of a UPC-market summed across retailers excluding the upc-retailer-market of the observation each month. Standard errors clustered on UPC, retailer, market, and month separately.

Table 2.4: Probability of price adjustment: linear probability model

	(1)	(2)	(3)	(4)
log revenue	0.0236	0.0207	0.0190	0.0234
	(0.00193)	(0.00145)	(0.00206)	(0.00213)
Observations	18,252,975	18,252,975	18,252,975	14,644,079
R-squared	0.042	0.083	0.131	0.132
Month FE	Y	Y	Y	Y
Market FE	N	Y	-	-
Retailer FE	N	Y	-	-
UPC FE	N	Y	-	-
UPC-retailer-market FE	N	N	Y	Y
Instrumental variable	N	N	N	Y
1st Stage F-stat	-	-	-	186.00

Note: The dependent variable is a binary variable with a value of one if the revenue from stores with price changes is larger than 17.6% of total revenue for a UPC-retailer-market in a given month. The independent variable of interest is the log of the total lagged revenue of a UPC-retailer-market each month. The instrumental variable is the log of the total lagged revenue of a UPC-market summed across retailers excluding the upc-retailer-market of the observation each month. Standard errors clustered on UPC, retailer, market, and month separately.

Table 2.5: Size of price adjustment

	(1)	(2)	(3)	(4)
log revenue	-0.0106	-0.0056	-0.0044	-0.0141
	(0.0003)	(0.0002)	(0.0002)	(0.0035)
Observations	2,484,753	2,484,753	2,484,753	2,394,461
R-squared	0.018	0.276	0.458	0.458
Month FE	Y	Y	Y	Y
Market FE	N	Y	-	-
Retailer FE	N	Y	-	-
UPC FE	N	Y	-	-
UPC-retailer-market FE	N	N	Y	Y
Instrumental variable	N	N	N	Y
1st Stage F-stat	-	-	-	11.50

Note: The dependent variable is the revenue-weighted average of the absolute size of price adjustment conditional on adjustment for a UPC-retailer-market in a given month. The independent variable of interest is the log of the total lagged revenue of a UPC-retailer-market each month. The instrumental variable is the log of the total lagged revenue of a UPC-market summed across retailers excluding the upc-retailer-market of the observation each month. Standard errors clustered on UPC, retailer, market, and month separately.

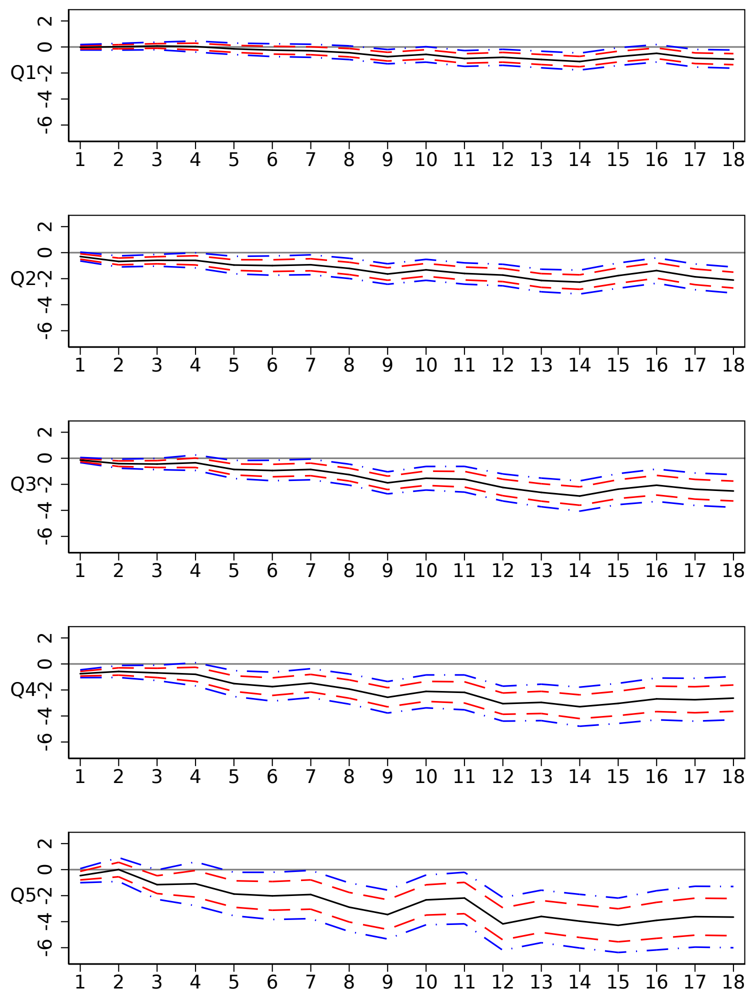


Figure 2.3: Cumulative price response to a monetary shock by revenue quantile
Note: This figure shows the cumulative impulse response of prices by revenue quantile, to an unexpected increase in the federal funds rate during a 30 minute window around FOMC announcements. Quantile 1 represents products with the lowest revenue and Quantile 5 represents those with the highest revenue. The dashed red lines represent one standard deviations confidence intervals. The dashed blue lines represent 90% confidence intervals.

Table 2.6: Revenue distribution over the business cycle

	(1) Mean	(2) Median	(3) Std deviation	(4) Spread
unemployment	-1.182	-1.333	-0.401	-1.033
rate	(0.348)	(0.382)	(0.112)	(0.308)
Observations	684,868	684,868	684,868	684,868
R-squared	0.814	0.787	0.542	0.561

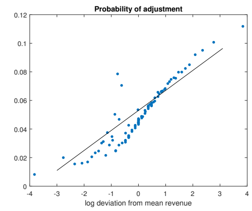
Note: The dependent variables are the moments of the log product revenue distribution across retailers for a given UPC-market-month. The independent variable of interest is the unemployment rate for a given market, computed from county level unemployment. All regressions include fixed effects for market, month, and product category. Standard errors clustered on market, month, and product category separately.

Table 2.7: Target moments

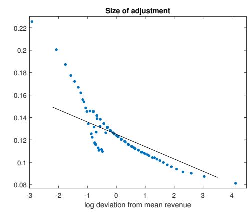
Steady state moments	**Target**	**Baseline** (k=0.3)	**Neutral** (k=1)
Frequency of price adjustment	0.067	0.067	0.067
Median size of price adjustment	0.104	0.102	0.112
Variance of log revenue	1.30	1.32	1.31
$\frac{\partial prob}{\partial lnrev}$	0.014	0.014	0.000
$\frac{\partial size}{\partial lnrev}$	-0.011	-0.011	-0.000
Business cycle moments			
$\frac{\partial \overline{rev}}{\partial N}$	1.18	1.18	1.18
$\frac{\partial rev_{50}}{\partial N}$	1.33	1.42	1.29
$\frac{\partial std(rev)}{\partial N}$	0.40	0.50	0.47
Persistence of real GDP	0.946	0.942	0.935
Standard deviation of real GDP	0.48%	0.50%	0.53%
Non-target moments			
Average size of price adjustment	0.148	0.105	0.111
$\frac{\partial (rev_{90} - rev_{10})}{\partial N}$	1.03	1.42	1.22
Average frequency - output relation	-0.068	0.069	-0.054

Table 2.8: Parameter values

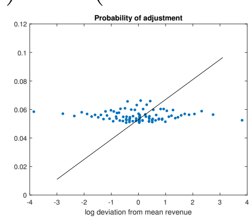
Parameter	**Baseline**	**Neutral**	**Description**
β	$0.96^{1/12}$	-	discount factor
ϵ	3	-	elasticity of demand
α	0.075	-	rate of product exit
$\bar{b}$	0.022	0.05	menu cost intercept
k	0.301	1	menu cost slope
χ	0.0127	-	probability of zero menu cost
$1-\theta_z$	0.146	-	probability of productivity shock
σ_z	0.085	-	standard deviation of productivity shock
σ_ι	0.152	-	standard deviation of demand shock
σ_m	0.52%	-	standard deviation of nominal GDP
ρ_ϕ	0.965	-	persistence of preference parameter
σ_ϕ	0.112%	-	standard deviation preference shock
ψ_0	1.2	-	slope parameter in exogenous demand
ψ_1	0.75	-	kink parameter in exogenous demand
ψ_2	2.15	-	intercept parameter in exogenous demand



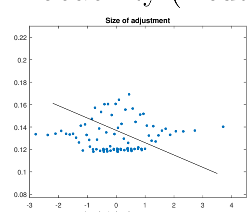
(a) Probability (Non-neutral)



(b) Size (Non-neutral)



(c) Probability (Neutral)



(d) Size (Neutral)

Figure 2.4: Revenue and price setting: comparing model and data

Note: In each panel, we group each product-month observation into percentile bins by revenue and compute the average revenue and the probability or absolute size of adjustment in each bin. We compute the log deviation of this revenue from the mean value, which we plot. The solid lines represent the calibration target, with a slope of 0.014 between log revenue and probability of adjustment and -0.011 between log revenue and absolute size of adjustment. Panels (a) and (b) represent the results from the baseline economy ($k < 1$), and Panels (c) and (d) represent the results from the neutral economy ($k = 1$).

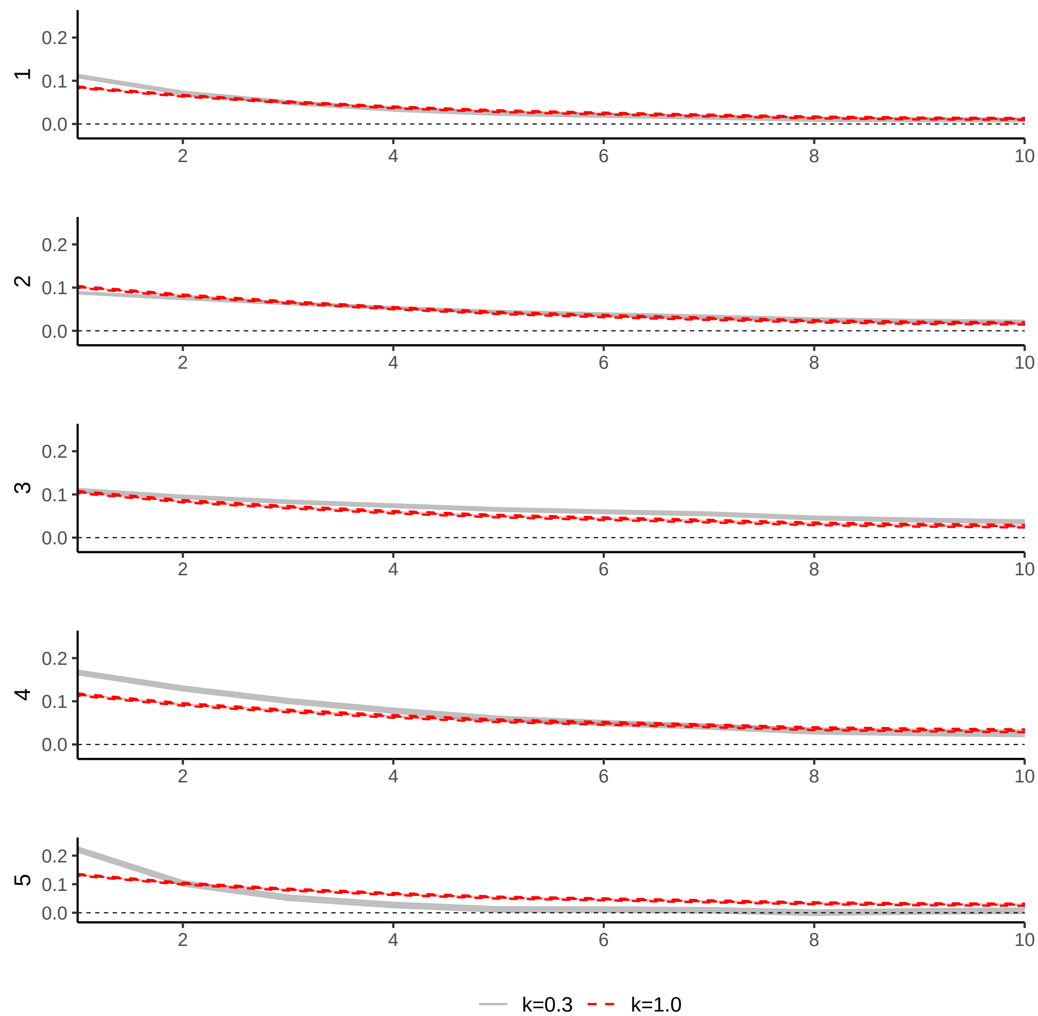


Figure 2.5: Impulse response of revenue-weighted average price change to a unit monetary shock by revenue quantile

Note: Each impulse response represents the response of each revenue quantile, with 1 being the lowest revenue products and 5 the highest revenue products. The gray line shows the impulse response function for the baseline economy. The red dashed line shows the impulse response function for the revenue neutral economy.

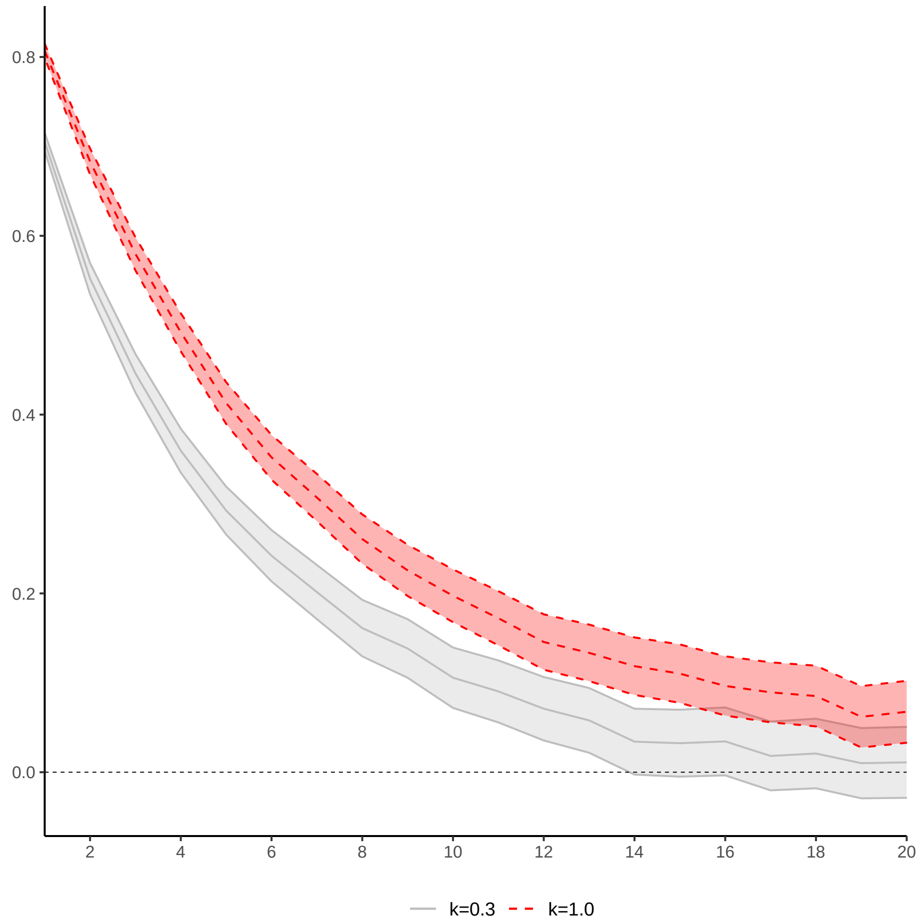
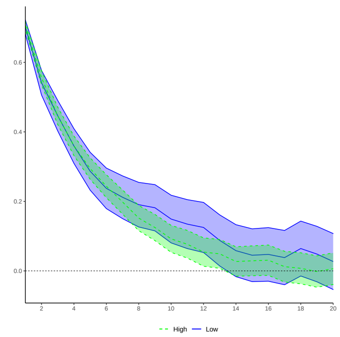
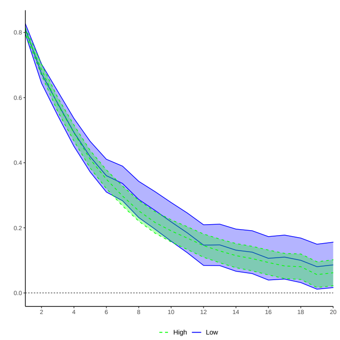


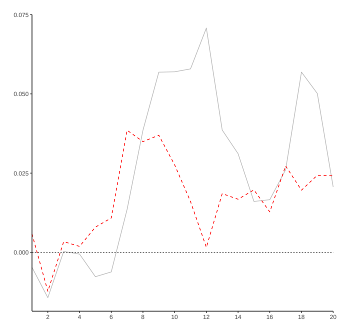
Figure 2.6: Impulse response of output to a unit monetary shock
Note: The gray line shows the impulse response function for the baseline economy. The red dashed line shows the impulse response function for the revenue neutral economy.



(a) Baseline



(b) Neutral



(c) Counter-cyclicality

Figure 2.7: State-dependence of output response to a unit monetary shock

Note: Panel (a) shows the impulse response for the baseline economy ($k < 1$). Panel (b) shows the impulse response for the revenue neutral economy ($k = 1$). The blue line in Panels (a) and (b) represent the impulse response of output in the low output state, defined as output in the bottom quarter of simulated periods. The dashed green line represents the output response in the high output state, which includes all states not defined as a low output state. Panel (c) shows the counter-cyclicality of the output response by computing the difference in the output response in a high versus low output state as a fraction of the impulse response in a high output state. The gray line plots the degree of counter-cyclicality for the baseline economy. The dashed red line does the same for the revenue neutral economy.

Table 2.9: Target moments : Extended model

Business cycle moments	**Target**	**Baseline**	**Ext.1**	**Ext.2**
$\frac{\partial \overline{rev}}{\partial N}$	1.18	1.18	1.33	1.37
$\frac{\partial rev_{50}}{\partial N}$	1.33	1.42	1.56	1.60
$\frac{\partial std(rev)}{\partial N}$	0.40	0.50	0.44	0.42
Persistence of real GDP	0.946	0.942	0.934	0.931
Standard deviation of real GDP	0.48%	0.50%	0.50%	0.50%
Average frequency - output relation	-0.068	0.069	-0.039	-0.072
Volatility parameter				
σ_d		0%	0.95%	1.25%

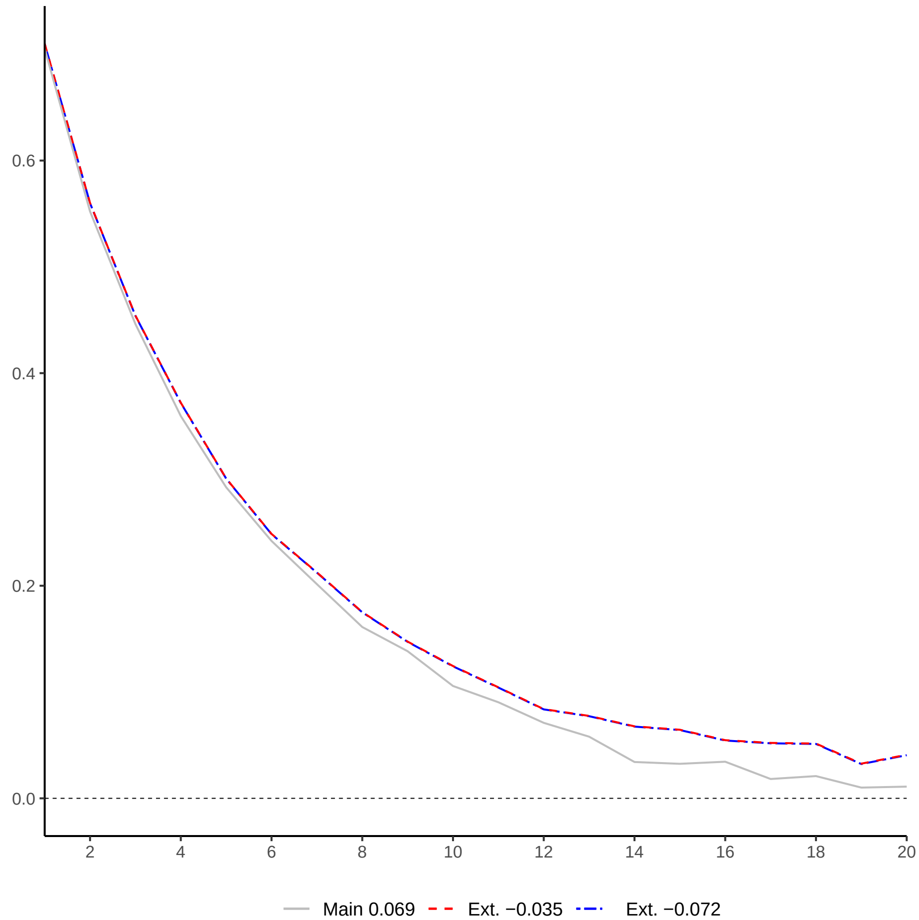


Figure 2.8: Impulse response of output to a unit monetary shock

Note: The gray line shows the impulse response function for the model economy without volatility shocks. The red dashed line shows the impulse response function for the economy where the frequency-output relation has a coefficient of -0.035. The blue dashed line shows the impulse response function for the economy where the frequency-output relation has a coefficient of -0.072.

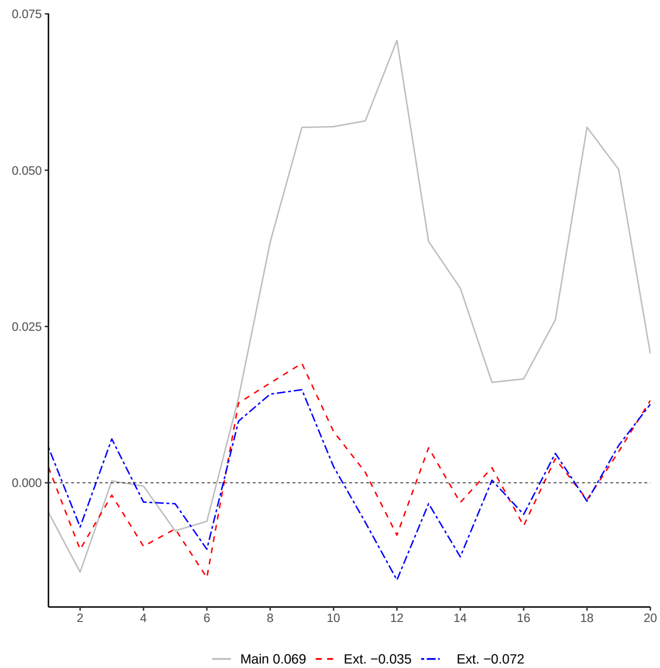


Figure 2.9: Counter-cyclicality of impulse response of output to a unit monetary shock

Note: We show the counter-cyclicality of the output response by computing the difference in the output response in a high versus low output state as a fraction of the impulse response in a high output state. The gray line plots the degree of counter-cyclicality for the baseline economy. The dashed red line does the same for the revenue neutral economy. The gray line plots the degree of counter-cyclicality for the model economy without volatility shocks. The red dashed line plots the degree of counter-cyclicality for the economy where the frequency-output relation has a coefficient of -0.035. The blue dashed line shows the degree of counter-cyclicality for the economy where the frequency-output relation has a coefficient of -0.072.

CHAPTER III

What Inventory Behavior Tells Us About Markups

3.1 Introduction

The increase in market concentration in several industries through the second half of the tweentieth[1] century has brought the literature to pay close attention to many of the changes that may accompany this. For example, Gutierrez and Philippon (2018) point to this as a possible culprit for underinvestmented. Autor et al. (2019) study the fall in the labor share resulting from increasing concentration due to heterogeneous productivity. The question of the degree of market power that firms hold because of this concentration is still open and the price markup, defined as the ratio between sale price and marginal cost, provides away to start answering it.

Given the difficulty to acquire good quality price and marginal cost information,

[1]See for example Gutierrez and Philippon (2018).

economist have resorted to estimate the price markup through several methods, making use of equilibrium and firm's optimization conditions. One of the favored methodologies when estimated the markup for several industries is based on Hall (1988) and makes use of the first order condition of the firms variable cost minimization problem. Notably, recent work by De Loecker et al. (2020) used this result, along with balance sheet firm data, to estimate the change in the economy-wide markup since the 1960's. In their results, they find that the price markup may have rise by as much as 60%. This finding, has sparked big interest in the topic because of the implications that a change of this magnitude would have.

Basu (2019) pointed out a concern with this estimation. A change in the price-markup of the magnitude found by De Loecker et al. (2020) should be accompanied by significant changes in the economy which are not aparent. Albeit, no estimation method is perfect and using the cost minimization first order conditions may have shortcomings. Mainly, the costs used in estimation should correspond to variable inputs of production. Two problems arrise with this assumption, first, the way firms keep their accounting records of cost may vary significantly. Having firms report some overhead fixed costs as cost of production when others may not. Second, some inputs used in production may not correspond to the cost of goods sold if the firms holds down inventories.

In this paper we look to contribute to the debate by looking at the change in price markup through a different first order condition. Based on Bils and Kahn (2000) we consider the problem of a firm that must hold inventories to produce sales. The first order condition of the firm ties down the price-markup to the ratio of the stock available to sales, an important statistic in the literature of inventories. Intuitively, the cost to the firm of missing a sale is given by the markup. In times when the markup is higher, the firm will want to hold larger quantities of inventories. This way, the stock to sales ratio, which is readily available from balance sheet data, provides information on the changes of the price markup.

In addition to the stock to sales ratio, our first order condition includes the expected growth rate of marginal cost. We use balance sheet data to estimate the firms production function to back out total factor productivity. This variable reflects both technology and input price changes and can be used to forecast the firm's marginal cost growth. Our first order condition, allows us to remain agnostic to changes in prices or market structure and the actual breakdown of the cost of production.

In our estimation, we find that the stock to sales ratio, accounting for changes in the productivity of the stock is decreasing through the entire period, as previously documented in the literature[2] However, the firms discounted marginal cost growth increases through time, due to a decreasing discount rate and a relatively flat marginal cost series. The combination of these factors point towards a slightly decreasing markup, with a fall of around 5% between 1970 and 2018. Most of the fall happens throughout the 70's and 80's decades and the series becomes relatively flat starting in the 2000's.

[2]see McConnell and Perez-Quiros (2000).

Two factors lead to the conclusion of falling markups. First, the falling stock to sales ratio reflects a smaller loss of the firm when a sale is not produced. This remains true even when adjusting for the increase in the productivity of the stock to produce sales. Second, the falling discount rate implies a falling cost of carrying inventories which should make the firm more willing to hold stock in order to produce sales. Our conclusion from this results is that further study of the importance of firm dynamics are necessary in order to understand the changes in the price-markup. Static first order conditions, while convenient, appear to be missing important information given the changes in the dynamic varibles of the firms problem, the stock available and the discount rate.

The structure of the paper is as follows: In Section 2 we present a theoretical framework in which firms hold a stock of the final good in order to produce sales and smooth the cost of production. Section 3 presents the methodology and results of the estimation of the adjusted stock to sales ratio and discounted expected growth in marginal cost. In section 4 we use the estimated series to back the changes in the price markup. Section 5 presents conclusions.

3.2 Theoretical framework

In this section we develop a model similar to Bils and Kahn (2000) in which firms hold inventories to facilitate sales. This is the current consensus reached in the literature, as it explains procyclical inventory investment. Inventories, or more specifically, the available stock, can facilitate sales by, for example, preventing stock-outs or allowing to match products with costumers. [3]. In our model sales of the final good consist of succesful matches between consumers and the available stock, a_t. The firm chooses both the available stock and price p_t before matching happens and after observing the aggregate state of the economy Θ_t. Given the stock, price and the aggregate state, consumers search for the product with an intensity $0 \leq d(p_t, \Theta_t) \geq 1$. Sales are determined by a matching function given by

$$s_t(p_t, a_t; \Theta_t) = d(p_t; \Theta_t) a_t^{\phi_t} \tag{3.1}$$

By construction $s_t \leq a_t$. The time-varying parameter $0 < \phi_t \leq 1$ is the elasticity of sales with respect to stock and represents how essential the stock available is to succesfuly match with consumers. To understand the nature of this parameter consider the perfect competition example where

$$d(p_t; \Theta_t) = \begin{cases} 1 & if \quad p_t = p_t^* \\ 0 & if \quad p_t \neq p_t^* \end{cases} \tag{3.2}$$

In this case, consumers will buy the product at the market price as long as they are succesfully matched with it. Matching will only depend on the stock available. Consider two types of firms, the first firm has a fixed share of the stock across its stores. The second firm has a distribution network between its stores, allowing to

[3]For a broader discussion of inventory investment behavior see for example Wen (2003).

move stock where necessary. Even if both firms produce the same stock a^*, the second firm will reach more consumers facilitating matches and sales, this is captured by a higher level of ϕ_t. The time variation in ϕ_t is due to changes in distribution and inventory management technology through time.

Let y_t be the level of production of the final good at a cost given by the function $C(y_t;\omega_t)$ where ω_t represents the realization of the firms idiosyncratic productivity. The stock available evolves according to

$$a_t = a_{t-1} - s_{t-1} + y_t \tag{3.3}$$

With the matching function 3.1 and assuming both aggregate state and productivity processes are first order Markov, the solution to the the profit maximization problem of the firm satisfies the following Bellman Equation subject to 3.1 and 3.3

$$V(a;\Theta,\omega) = \max\{ps - C(y;\omega) + E[\beta V(a';\Theta',\omega')]\} \tag{3.4}$$

Here β represents the realization of the stochastic discount factor. Let c_t be the marginal cost of production of the firm in period t. The first order conditions of the firm's problem are

$$1 = \phi_t \frac{s_t}{a_t}\frac{p_t}{c_t} + \left(1 - \phi\frac{s_t}{a_t}\right) E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] \tag{3.5}$$

$$1 = \xi_t p_t E\left[1 - \beta_{t+1}\frac{c_{t+1}}{p_t}\right] \tag{3.6}$$

Where ξ is the price elasticity of the search intensity function $d(p_t;\Theta_t)$. Notice that the search intensity function $d(p_t;\Theta_t)$ appears in equation 3.5 only through the ratio of sales to the stock available $\frac{s_t}{a_t}$, which is observable in the data. Focusing on equation 3.5 allows us to remain agnostic to the shape of $d(p_t;\Theta_t)$, meaning equation 3.5 remains valid under any type of market structure that can be modelled in this way. This includes the cases of perfect competition and monopoly.

The derivative of sales with respect to the stock available is $\phi_t \frac{s_t}{a_t}$ so we can rearrange equation 3.5 as follows to get an interpretation. At the optimal choice of a_t a perturbation Δa_t must be such that the change in costs equals the change in revenue,composed by the fraction of Δa_t sold at a price of p_t and the fraction kept in inventory with a shadow value of $E\left[\beta_{t+1}c_{t+1}\right]$.

$$c_t \Delta a_t = \frac{\partial s_t}{\partial a_t}\Delta a_t p_t + \left(1 - \frac{\partial s_t}{\partial a_t}\right) E\left[\beta_{t+1}c_{t+1}\right]\Delta a_t$$

Using equation 3.5 we can study changes in the price markup through the changes in the other firm-level variables connected to it. Solving for $\frac{p_t}{c_t}$ yields

$$\frac{p_t}{c_t} = \frac{1}{\phi_t}\frac{a_t}{s_t} - \left(\frac{1}{\phi_t}\frac{a_t}{s_t} - 1\right) E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] \tag{3.7}$$

Lets assume that marginal cost is constant (or decreasing) through time, so that $E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] < 1$. In that case the equilibrium markup holds a strictly positive relation with $\frac{1}{\phi}\frac{a_t}{s_t}$. The markup is the forgone benefit when a match fails hence, in times when the markup is high, the firm wants a higher stock relative to sales in order to succesfully match. Additionaly, changes in technology represented by ϕ_t affect the relation between the stock to sales ratio and the markup. At a given markup, if ϕ_t becomes higher, meaning the firm is better at converting stock into sales, the firm will hold a lower stock.

As we can see, the changes in markup in the last four decades can be infered by the changes of these three variables, the stock-to-sales ratio, the expected change in marginal cost, and the elasticity ϕ_t. In the following section we will look at the historical behavior of this variables and work our way to the implication for the price markup.

3.3 Historical look of the firms' production

In this section we use annual firm level data from Compustat for the period between 1970 and 2017, to recover or estimate the variables connected to the price markup. We assume the firm has a production technology that takes variable inputs, L and capital, K given by

$$Y_{it} = e^{\omega_{it}} L^{\alpha_j^L} K^{\alpha_j^K} \tag{3.8}$$

The production function parameters vary by industry as classified by two digits NAICS codes. There is no constraint on returns to scale through the parameters, we allow them to take any positive value.

3.3.1 Firm's forecast of marginal cost growth

The last term in equation 3.7 is the expected growth of discounted marginal cost for the firm. We take the stance of modeling this as a forecast made by the firm with the information available until the moment of the forecast. Two components enter these value, the stochastic discount factor and the growth rate of marginal cost. For a given stock-to-sales ratio, the price markup is decreasing in both of them. If marginal cost is higher in the future, the firm will choose to keep a higher stock for cost-smoothing purposes, even if the markup is high.

We assume that for the forecast, the firm treats the stochastic discount factor and the marginal cost growth rate as independent so that

$$E\left[\widehat{\beta_{t+1}\frac{c_{t+1}}{c_t}}\right] = E\,[\hat{\beta}_{t+1}]E\left[\widehat{\frac{c_{t+1}}{c_t}}\right] \tag{3.9}$$

A firm forecasts the stochastic discount factor through its current financing cost, r_t^f. Simply put, we assume the firm chooses to discount future values using its time cost of funds. We compute real financing costs, as the ratio between "Interest and related expenses" and the firms total debt minus inflation[4]. Figure 3.1 shows in panel (a) the average $\beta_t = (1+r_t^f)^{-1}$, weighted by sales, from 1970 to 2018. Notably, financing costs have steadily declined through these five decades to the point where the financing rate is below inflation. On average, for the last few years in our sample, the average financing rate is about half a percentage point lower than inflation. As

[4]Inflation is obtained through the GDP deflator

a result, the discount factor used by the firm has increased mostly increased during this period, with a few sharp declines corresponding to major recessions, as indicated by shading.[5]. Starting in 2004, the discount rate has been often above one, reflecting a financing rate below inflation.

On panel (b) of Figure 3.1 we show estimated densities for the distribution of discount factor (x-axis) across firms. In 1975, the density is almost centered a little above 0.9 while for 2005 and 2015 most of the mass has shifted towards higher values. The quick take of this graph is that the financing rates of all firms in the sample have decreased in this period as opposed to just the average rate. Further, the dispersion in rates has decreased as well, meaning most firms access similar lower rates.

The second component of the firm's forecast is the expected growth rate of marginal cost. Given the production function 3.8, marginal cost for firm i in industry j at time t is given by

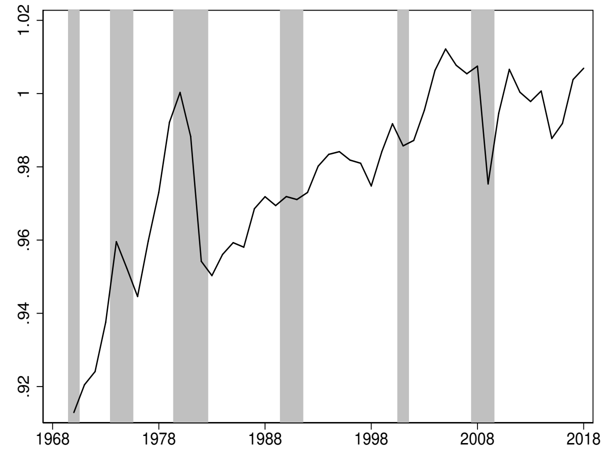
$$c_{it} = e^{-\omega_{it}} \left(\frac{P_{it}^{L}}{\alpha_j^{L}} \right) \left(\frac{P_{it}^{K}}{\alpha_j^{K}} \right) \tag{3.10}$$

As mentioned above, L represents variable inputs rather than just labor. We assume that for the firm forecast, only productivity is expected to change from the current year. This is, $E\left[P_{it+1}^{L}\right] = P_{it}^{L}$ and $E\left[P_{it+1}^{K}\right] = P_{it}^{K}$. Implicitely, we are also assuming that the firm considers its forecasts for productivity and input prices to be independent, so we treat them as multiplicatively separable through the expectation

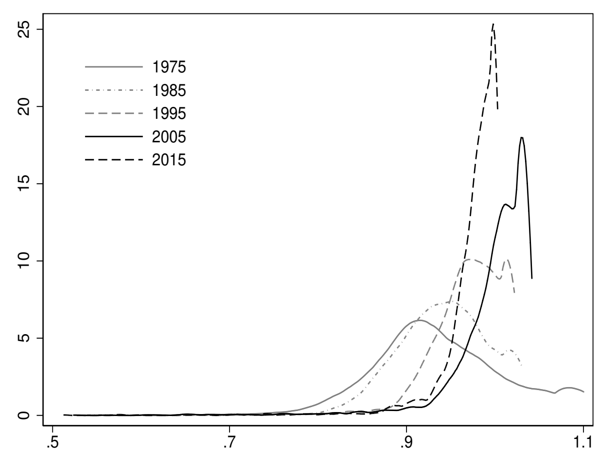
[5]A year is shaded if the economy was in recession for at least one quarter according to NBER recession dates.

Figure 3.1: Firms real discount factor from financing costs

Sales-weighted average



Firm distribution



operator. Under these assumptions we have that

$$E\left[\frac{c_{t+1}}{c_t}\right] = E\left[e^{\omega_{it}-\omega_{it+1}}\right]$$

We follow the procedure in **?** to estimate the parameters of the production function by industry. We recover the values of productivity as

$$\hat{\omega}_{it} = (y_{it} - \hat{\varepsilon_{it}}) - \hat{\beta}_j^K K_{it} - \hat{\beta}_j^L P_{it}^L L_{it} \tag{3.11}$$

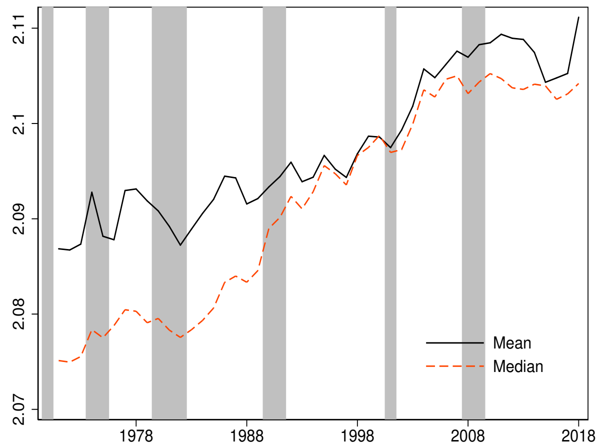
Let FGI_{it} be the final good inventories at the end of year t. The stock available is $a_{it} = s_{it} + FGI_{it}$. Com bining this with equation 3.3 we can compute production $y_{it} = s_{it} + FGI_{it} - FGI_{it-1}$. The correction term $\hat{\varepsilon}$ corresponds to the etimated error from the first stage of the ACF procedure. We use “cost of goods sold” for the value of $P_{it}^L L_{it}$. Panel (a) of Figure 3.2 shows the sales-weighted average and median of our estimated productivity series. The productivity series increases steadily through the period of our sample. However, for both average and median, the total increase in the period is very modest, at around one percentage point. This points towards a flat series of expected growth in marginal cost. There is no evident cyclical behavior in the productivity series.

Having the productivity series $\hat{\omega}$, we build a forecast of marginal cost with a second order polinomial regression with firm and year fixed effects. The estimated equation is given by

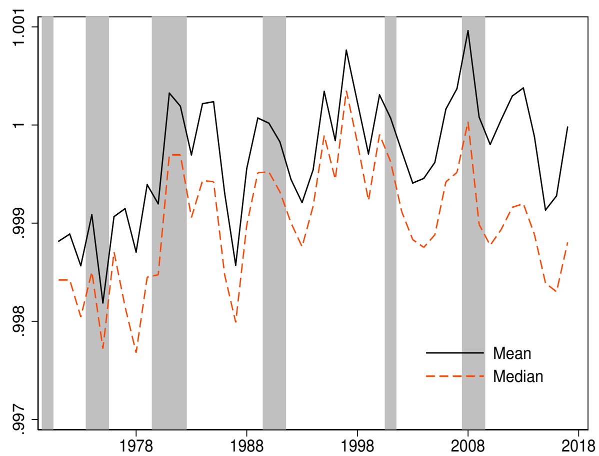
$$c_{it+1} = \gamma_i + \gamma_t + \rho_1 c_t + \rho_2 c_t^2 + u_{it+1} \tag{3.12}$$

Figure 3.2: Firm's forecast of productivity and marginal cost growth

Sales-weighted average productivity



Sales-weighted average marginal cost growth

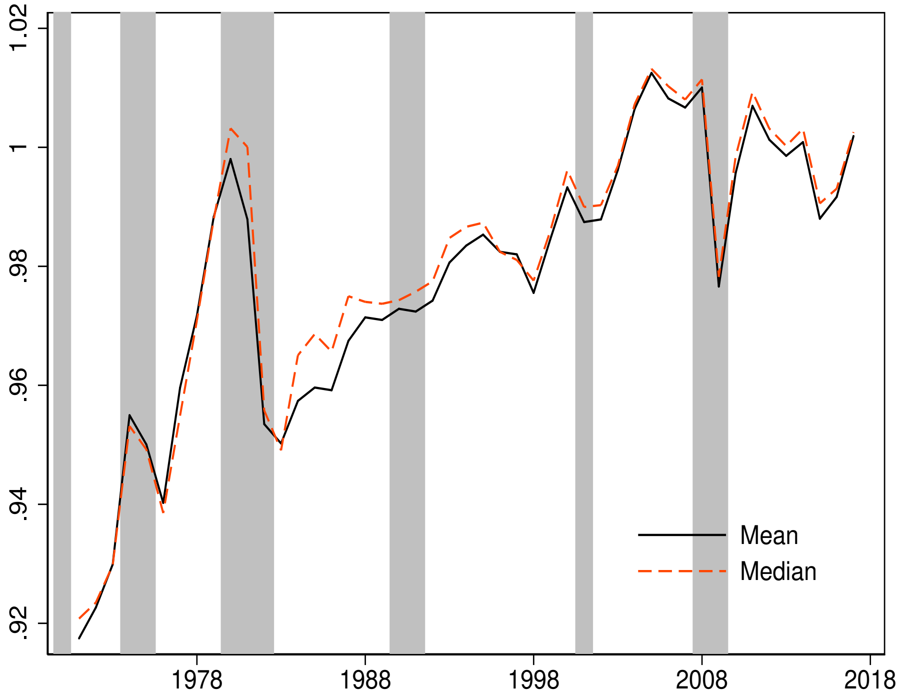


We follow Blundell and Bond (1998) , instrumenting with lag-differences of the dependent variable. Panel (b) of Figure 3.2 shows the sales-weighted average and median of the estimated growth in marginal cost. As foreshadowed by our productivity series, the estimate for expected marginal cost growth is very flat through the entire period. Figure 3.3 shows the estimated series of discounted expected marginal cost growth. The contribution of the discount factor β dominates, making the series steadily increasing through the period. This result provides the first component of our markup estimation. From equation 3.7 we have that, holding everything else constant, the markup is strictly decreasing in the discounted expected marginal cost growth. Our result in this section puts pressure towards a decreasing markup in our sample period.

3.3.2 Stock-to-sales ratio

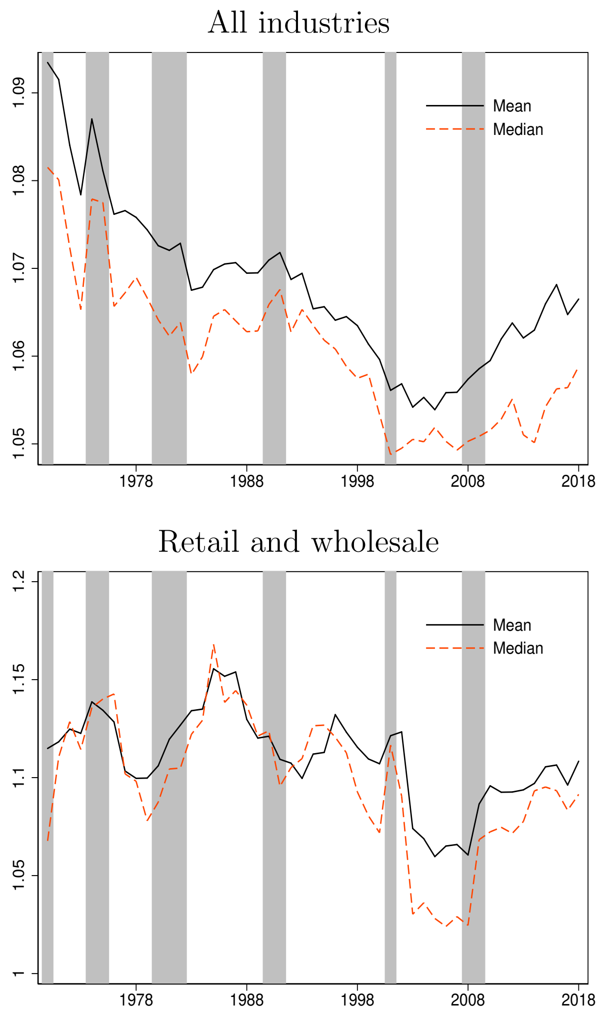
The next component in our markup estimation is the ratio between the available stock and the sales of the production good. This variable holds the key intuition of this paper. If markups are increasing, the loss faced by the firm from a stockout is also increasing. Everything else constant, a firm will increase the available stock relative to sales to prevent stockouts as they become costlier. Figure 3.4 shows the sales-weighted average of the ratio for all industries on panel (a). Consistent with the literature, the ratio falls from the seventies and through the great moderation, reaching a through in the mid-2000's. There is a modest recovery of the ratio in the last decade of the sample, the period after the great recession. In panel (b), we show that this behavior is not present in all industies. In the case of retail and wholesale

Figure 3.3: Firm's forecast of expected discounted growth in marginal cost



trade, there is no obvious decline in the ratio. These are industries with higher dependence on inventories, as evidenced by the larger average value and volatility of the ratio when compared to the rest of the economy.

Figure 3.4: Ratio of available stock to sales



Equation 3.7 shows a positive relation between the markup and the ratio of available stock to sales as long as $E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] < 1$. Figure 3.3 shows that this is the case

on average in our data up until 2003. From 2004 onwards, our data suggests a negative relation between the markup and stock to sales ratio. This point to a markup that should be decreasing through the entire sample period, if every other component in equation 3.7 is held constant. However, in the case of retail and wholesale trade, the industries for which are model should fit best, we dont see this obvious decline of the ratio. Additionaly, it is still necesary to look at was has happened to ϕ, the technology that allows firms to turn available stock into sales.

3.3.3 The elasticity of sales with respect to available stock

In this part we estimate the elasticity of sales with respect to available, ϕ. We estimate the following specification as in Blundell and Bond (1998), instrumenting with lagged differences of the variables to correct for bias in the autorregresive coefficient.

$$ln(a_{it}) = \gamma_i + \gamma_t + \rho ln(a_{it-1}) + \frac{1}{\phi} ln(s_{it}) + u_{it} \tag{3.13}$$

Table 3.1 shows the estimated values for the entire period in the first column. Our estimate of *phi* for the entire sample is around 0.85. Lower values of *phi* mean that the firm requires a higher stock available to produce sales. Given this value of ϕ even under a setup in which consumers are always willing to buy the good at market price $d(p_t^*) = 1$, as in the example in Section 2, a firm with a stock of a will be left with $a^{0.85}(a^{0.15}-1)$. As ϕ approaches 1, the firm does not require inventories to make a sale, however, a monopolist firm can still choose to carry inventories by choosing p_t so that $d(p_t) < 1$. From equation 3.7 we can see that increasing ϕ increases the importance of the marginal cost ratio for the markup. This is because as the firm stops requiring inventories to produce sales, it can use inventories to smooth costs of production through time.

Table 3.1: Dynamic panel estimates of the elasticity of sales to stock available

	Full sample	pre 2000	post 2000
ρ	-0.17	-0.46	-0.12
	(0.06)	(0.46)	(0.04)
$\frac{1}{\phi}$	1.18	1.47	1.12
	(0.06)	(0.46)	(0.04)
Obs.	87,523	45,755	41,768

The second and third columns show estimates of ϕ, dividing the sample before and after the year 2000. For the first period, from 1970 to 1999, the estimate of ϕ is around 0.68. For the second part it increase to about 0.89. This is consistent with the changes in distribution and sales technology of the past decades. The need of the firm to hold inventories to produce sales has decreased considerably. Firms need lower ratios of stock available to sales, everything else equal. For example, a firm that wanted to sell 2 units before 2000 would need an available stock of 2.77 units, delivering a ratio of available to sale of 1.39. After the year 2000, the stock available required to sell 2 units is 2.17 and the ratio 1.09. This increase in ϕ allows to accomodate the decrease in the stock to sales ratio even if markups were increasing.

3.4 The price markup

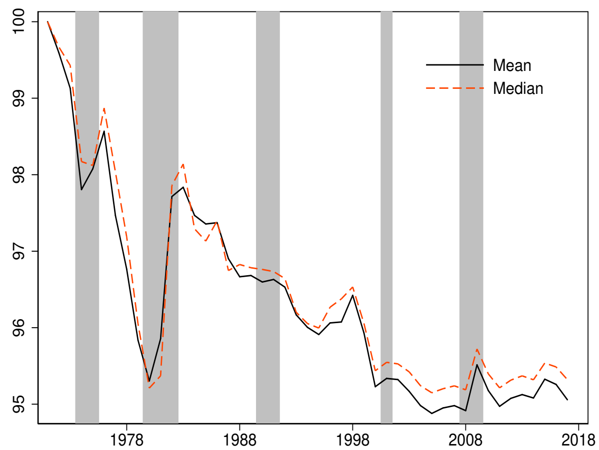
Following equation 3.7 we estimate the change in the markup through our sample with the variable estimates from the previous section. We split the value of ϕ as estimated, inputing one value for firms before the year 2000 and another one afterwards. Figure 3.5 shows the estimated markup considering both a change in ϕ (panel (a)) and holding it constant (panel (b)). In both cases we see a mild decrease in the markup over the period. Considering a change in ϕ the markup decreases about 5% and becomes relatively constant starting in the 2000's. With a constant ϕ the drop is weaker of about 2.5% points. These are the results of a decreasing stock to sales ratio combined with a ratio of marginal cost thats both increasing and less than unity for most of the years in our sample. After, the ratio of marginal cost becomes higher in the 2000's we see a markup that starts slightly recovering.

Our result that markups have fallen over the last 40 years is in contrast to much of the literature, we are working on allowing for more flexible changes in the matching technology. Additionally, we are working on investigating the industries that most closely match our intuitive understanding of inventories. The model should have more validity for industries that hold physical inventories.

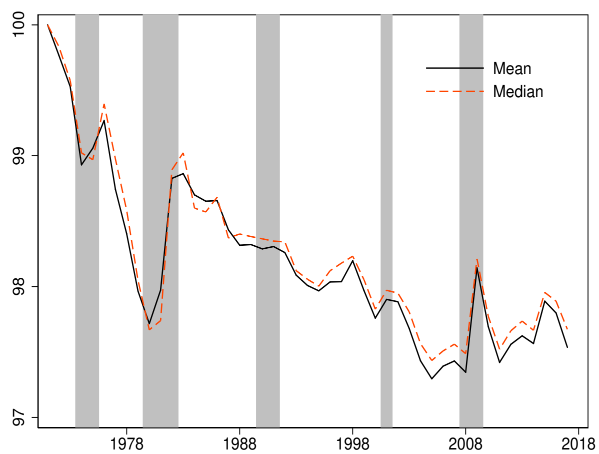
The fact that the discount rate of the firm decreases steadily produces an increasing discounted marginal cost growth. It is cheaper for firms to hold inventories as the rate goes down, making it relatively cheaper to produce presently. The decreasing cost of holding inventories together with the decrease in the stock to sales ratio

Figure 3.5: Changes in price markup, index

One change in ϕ



Constant ϕ



implies that the relative cost to the firm of loosing a sale is decreasing, leading to the conclusion of a falling markup.

3.5 Conclusion

The theoretical framework of our paper shows that some of the firm's dynamic variables play an important role when determining the price-markup. If the firm is able to hold inventories, the change in the discounted marginal cost of production in the future becomes relevant fot the firms decision to sell at a certain price. If the discounted marginal cost of production is increasing, the firm can hold on to sell presently and accumulate stock of the final good. However, firms in the sample are constantly reducing the relative stock of final goods. This fact, follows partially from lower need to hold stock in order to produce sales, as distribution and inventory technology has become better. This last fact is not enough to rationalize the fall in the relative stock, menaing that additionaly, the cost to the firm of loosing a sale must be decreasing, at least slightly. This cost is refelcted by the price-markup, as a firm looses this value when failing to complete a sale. The historical behavior of both stock and discounted marginal cost are hard to reconcile with a scenario in which markups are increasing. If markups are indeed growing, further work on the firm's dynamic problem is necessary to understand the puzzling behavior of the stock and cost.

APPENDIX A

Appendix For Chapter I

Markets

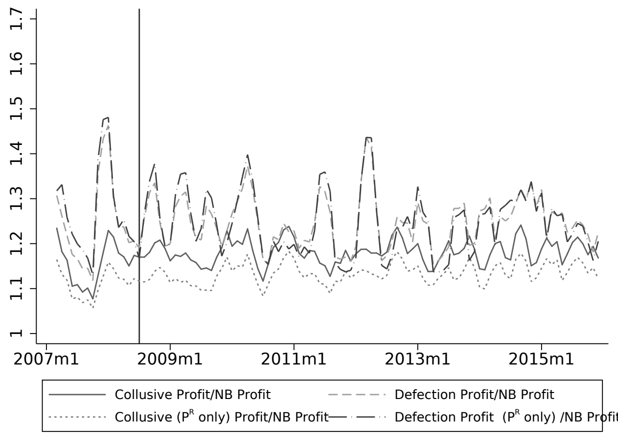
We choose 32 markets on which we conduct our analysis. The designated market areas are defined by The Nielsen Company and correspond approximately (although not exactly) to a metropolitan statistical area (MSA). The full list is provided in Table B.3.

Table A.1: Designated Market Areas

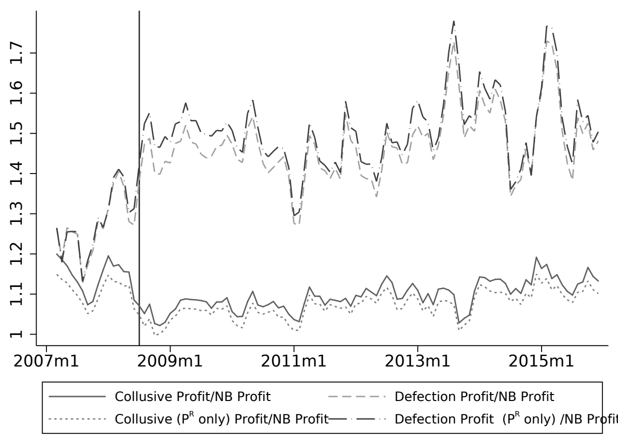
DMA Name
Portland-Auburn ME
New York NY
Philadelphia PA
Detroit MI
Boston (Manchester) MA-NH
Ft Wayne IN
Cleveland OH
Washington DC (Hagerstown MD)
Baltimore MD
Cincinnati OH
Charleston SC
Atlanta GA
Indianapolis IN
Louisville KY
Hartford & New Haven CT
Tampa-St Petersburg (Sarasota) FL
Raleigh-Durham (Fayetteville) NC
Chicago IL
St Louis MO
Minneapolis-St Paul MN
Kansas City MO-KS
Oklahoma City OK
Omaha NE
Nashville TN
Wichita-Hutchinson Plus KS
Des Moines-Ames IA
Little Rock-Pine Bluff AR
Denver CO
Phoenix AZ
Boise ID
Albuquerque-Santa Fe NM
Los Angeles CA
San Francisco-Oakland-San Jose CA
Seattle-Tacoma WA

Figure A.1: Inputs to Discount Factor

(a) Budweiser



(b) Miller



(c) Coors

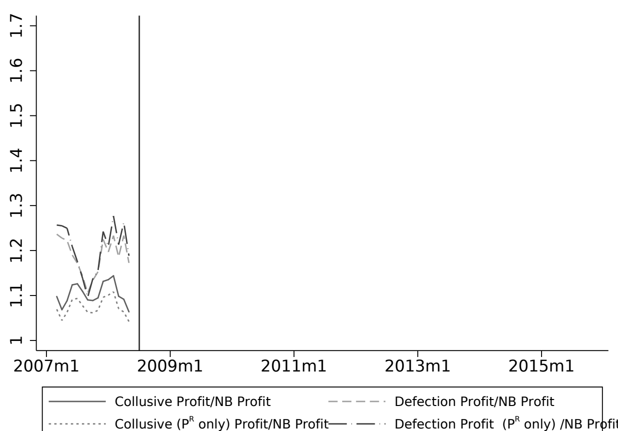
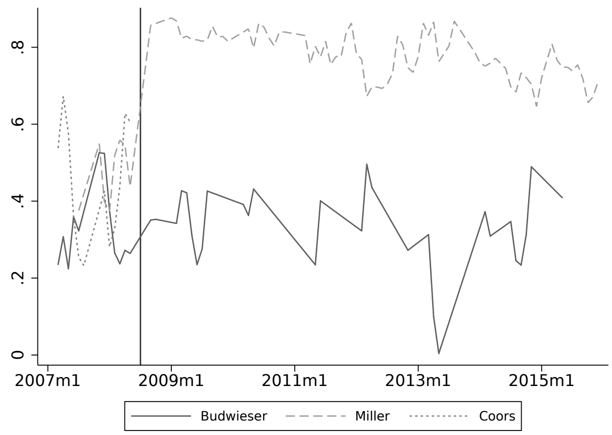
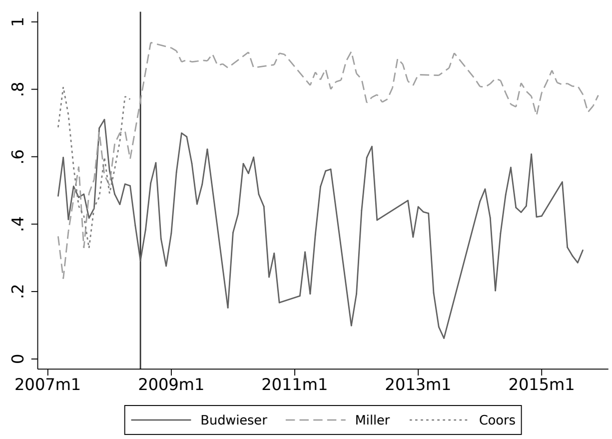


Figure A.2: Discount factor by firm

(a) Sales equilibrium



(b) No-sales equilibrium



APPENDIX B

Appendix For Chapter II

Exogenous Adjustment Hazards

Let $\Lambda(x)$ be a function representing the exogenous adjustment hazard of a firm with price gap x, perhaps due to an exogenous shock to menu cost. Let $\tilde{F}(x), \tilde{f}(x)$ be the distribution of price gaps before adjustment via $\Lambda(x)$ and $F(x), f(x)$ be the distribution of price gaps post adjustment via adjustment hazard. This implies that $f(x) = (1 - \Lambda(x))\tilde{f}(x)$ with mass equal to $\int \Lambda(x)\tilde{f}(x)dx$ at $x = 0$. Assuming that $\Lambda(x)$ is independent of revenue, the following equations hold.

$$prob(rev^*) = F(-\zeta(rev^*)) + (1 - F(\zeta(rev^*))) + \int \Lambda(x)\tilde{f}(x)dx \tag{B.1}$$

$$size(rev^*) = \frac{1}{prob(rev^*)}\Big\{ \int_{-\infty}^{-\zeta(rev^*)} (-x)f(x)dx + \int_{\zeta(rev^*)}^{\infty} xf(x)dx + \int |x|\Lambda(x)\tilde{f}(x)dx\Big\} \quad \text{(B.2)}$$

The equations governing the relationship with revenue are derived as follows,

$$\frac{\partial prob(rev^*)}{\partial ln(rev^*)} = \frac{1-k}{2} \cdot \zeta(rev^*)[f(-\zeta(rev^*)) + f(\zeta(rev^*))] \quad \text{(B.3)}$$

$$\frac{\partial size(rev^*)}{\partial ln(rev^*)} = \frac{\partial prob(rev^*)/\partial ln(rev^*)}{prob(rev^*)}\Big\{\zeta(rev^*) - size(rev^*)\Big\}. \quad \text{(B.4)}$$

$$\text{(B.5)}$$

Equations (B.3) and (B.4) are identical to equations (2.6) and (2.7).

Suppose the monetary shock Δm occurs after distribution $\tilde{f}(x)$ has been realized. (This is equivalent to an assumption about the independence of the monetary shock to the adjustment hazard.) Then the expected price change is,

$$\int \Delta lnp(x, \Delta m; rev^*)f(x)dx = \int_{\zeta(rev^*)+\Delta m}^{\infty} -(x-\Delta m)f(x)dx + \int_{-\infty}^{-\zeta(rev^*)+\Delta m} -(x-\Delta m)f(x)dx + \int -(x-\Delta m)\Lambda(x-\Delta m)\tilde{f}(x)dx.$$

The expected price response to an arbitrarily small monetary policy shock is,

$$\begin{aligned}
\mathcal{A}(rev^*) &= F(-\zeta(rev^*)) + (1 - F(\zeta(rev^*))) + \int \Lambda(x)\tilde{f}(x)dx \\
\mathcal{E}(rev^*) &= \zeta(rev^*) \cdot [f(-\zeta(rev^*)) + f(\zeta(rev^*))] + \int x\Lambda'(x)\tilde{f}(x)dx \\
&= \frac{2}{1-k} \cdot \frac{\partial prob}{\partial ln(rev^*)} + \int x\Lambda'(x)\tilde{f}(x)dx
\end{aligned}$$

Note that as before $\mathcal{A}(rev^*) = prob(rev^*)$.

Then the relationship between product revenue and the intensive margin, extensive margin, and the responsiveness of prices to monetary policy can be derived respectively as follows:

$$\frac{\partial \mathcal{A}(rev^*)}{\partial ln(rev^*)} = \frac{\partial prob(rev^*)}{\partial ln(rev^*)}. \tag{B.6}$$

$$\frac{\partial \mathcal{E}(rev^*)}{\partial ln(rev^*)} = -\Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)\Big[1 + \zeta(rev^*)\frac{f'(\zeta(rev^*)) - f'(-\zeta(rev^*))}{f(\zeta(rev^*)) + f(-\zeta(rev^*))}\Big] \tag{B.7}$$

$$\frac{\partial \mathcal{F}(rev^*)}{\partial ln(rev^*)} = \Big(\frac{\partial prob(rev^*)}{\partial ln(rev^*)}\Big)\zeta(rev^*)\Big(\frac{-f'(\zeta(rev^*)) + f'(-\zeta(rev^*))}{f(\zeta(rev^*)) + f(-\zeta(rev^*))}\Big) \tag{B.8}$$

Note that equations (B.6), (B.7), and (B.8) are identical to the case without the adjustment hazard.

Estimating Menu Cost Parameters

In this appendix we describe how we estimate the parameters of the menu cost function that we use in Table 2.8 of Section 2.4. We use the simple model described in Section 2.2 and Appendix B to generate simulated price changes and compare features of the data to the simulation results. This allows us to estimate the relationship between menu costs and revenue. We find that menu costs scale less than one-to-one with revenue.

Firms change prices for two reasons. First, with probability χ, random shocks arrive that temporarily make price adjustment costless. This is standard in the literature to fit small price changes. Absent these shocks, firms compare the menu cost with the loss from a sub-optimal price. We assume the menu cost has the functional form, $\bar{b}(rev^*)^k$. The main purpose of this section is to estimate the parameters k and χ.

We target two features of the data. First, from our data, we take observed revenue for each product and remove time, product, and retailer-market fixed effects. We then sort the products by this residual revenue $r\hat{e}v_{ijt}$ into deciles $d = 1, 2...10$. For each decile, we calculate the average frequency of price change $f\bar{r}eq_d$. In addition, within each decile, we estimate a density of observed price changes $f_d^{pc}(.)$ via a kernel density estimation. We estimate the density at 201 grid points (index by m) using a Gaussian kernel and the fixed bandwidth of .025. These features are the targets of the estimation.

The model we use to generate pricing simulations is a parametric version of the model in Section 2.2 and Appendix B. Given a revenue distribution and a distribution of price gaps, we compare the menu cost to the loss from suboptimal price using equation (2.2) and generate the frequency of adjustment and the distribution of price changes. We assume that revenue follows a log-normal distribution in every decile and that the price gaps follow a two parameter Gamma distribution. We do this to allow a relatively flexible distribution of observed price changes, which we then compare to the data.

Thus the following parameters govern the distributions and the behavior of the firms: μ_x the shape parameter of the distribution of price gaps, σ_x the scale parameter of the distribution of price gaps, $\bar{b}$ the intercept and k the slope of log revenue in the menu cost expression, and χ the probability of zero adjustment costs. Together we denote these parameters as Θ. In addition, we use the calibrations outlined in Table B.1 (from Section 2.4) to generate both a distribution of revenue and the losses associated with each price gap. We fix the bandwidth for non-parametrically estimating the densities of the size of price changes at 0.025.

We estimate the parameters Θ to minimize the difference in the average frequency and price change distributions of each decile. We minimize the loss function:

$$\begin{aligned}\mathbb{L}(\Theta) = & (1-W)\frac{1}{10}\sum_d (\hat{\bar{freq}}(\Theta)_d - \bar{freq}_d)^2 \\ & + \frac{1}{10 \times 201}\sum_d \sum_m (\hat{f}^{pc}_{d,m}(\cdot;\Theta) - f^{pc}_{d,m}(\cdot))^2 * f^{pc}_{d,m}(\cdot).\end{aligned}$$

The first term is the sum across deciles of revenue of differences between the frequency of price change in the simulation and the data. The second term is the of sum the square of the differences between the density within each decile of revenue evaluated at each of the grid points. Each summand is weighted by the empirical density at that grid point, this is to ensure that the parts of the distribution that are most frequently seen are given higher weight. The two terms are weighted by a fixed $W = 0.01$ which gives most of the weight to the average frequency term.

In order to generate the simulated price changes, we randomly draw revenue and price gaps from Lognormal and Gamma distributions respectively, for 1,000,000 simulated firms. After each draw, the firms immediately adjust their price (close their price gap) with probability χ. For every firm not changing from this shock, we compare the menu cost to the loss from the sub-optimal price and adjust when the loss from suboptimal pricing is larger. We compute by decile of revenue the average frequency of price change: $\hat{freq}(\Theta)_d$ and the distribution of observed price gaps in each decile $\hat{f}_d^{pc}(\cdot;\Theta)$. This simulation gives us a distribution of price changes for each set of parameters Θ. We search across values of Θ to find the minimizer of $\mathbb{L}(\Theta)$.

We present the estimated parameters in Table B.2. We find evidence that the menu cost is sub-linear in revenue ($k = 0.301$); that is that the menu cost grows less than one-to-one with revenue. Additionally, we find that the probability of zero menu cost is 1.27%. Together with χ and k, we estimate scale and shape parameters of the Gamma distribution as well as $\bar{b}$. While these parameters are useful in evaluating the model, we do not use them in the main model section of this paper. First, the scale and shape parameters are redundant as the main model generates price gap distributions from dynamic choices. Secondly, $\bar{b}$ is closely tied to the average frequency of price changes; we allow the main model to be disciplined directly by that moment.

In Figure B.1 we show the distribution of the price gaps generated from the model compared to the data. In Figure B.2, we compare the distribution of observed price changes generated by the model compared to the data. We fit the shape of the relationship between revenue and frequency of price changes relatively closely and the distribution of price gaps at each decile of revenue less well, while still capturing the general relationship with revenue apparent in the data.

Overall, we make a serious effort to estimate the parameters of the menu cost function and take the results as inputs to the quantitative parts of this paper. However, we do not claim they are authoritative, and future work may be warranted. We believe that we are the first to propose estimating this relationship between menu costs and revenue.

Table B.1: Calibrated parameters for the estimation the menu cost function

parameter	value	
μ_{rev}	0	Mean parameter of the normal for revenue
σ_{rev}	1.3	Variance parameter of the normal for revenue
ϵ	-3	Price elasticity
bw	.025	Bandwidth for size of change

Table B.2: Estimation results

parameter	value	
k	0.301	menu cost exponent
$\bar{b}$	0.00727	menu cost level-shifter
χ	0.0127	probability of free change
μ_x	0.108	Shape parameter of the Gamma for price gaps
σ_x	0.102	Scale parameter of the Gamma for price gaps

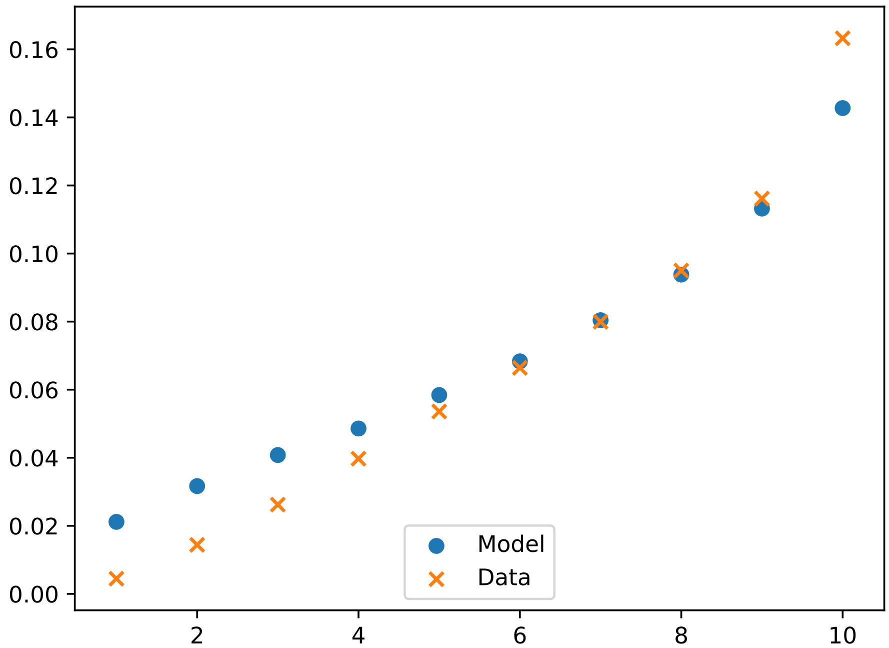
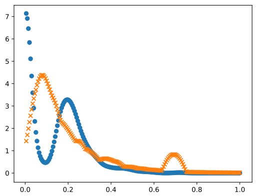
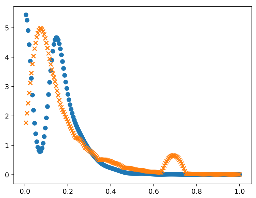


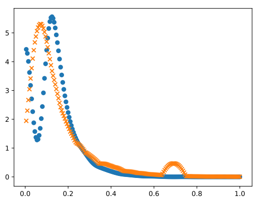
Figure B.1: Frequency of price change by decile of residualized revenue
Note: This figure shows the fit of the estimated menu cost model. The deciles are constructed from residual revenue. Blue dots represent the simulated results from the model and the orange x represents the data.



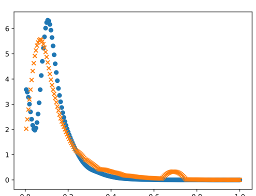
(a) 1st



(b) 2nd



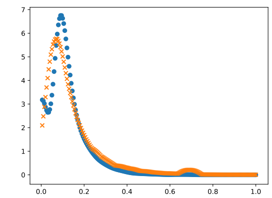
(c) 3rd



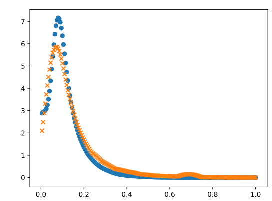
(d) 4th

Figure B.2: Distribution of price changes by decile of revenue

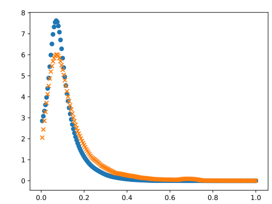
Notes: This figure shows the fit of the estimated distribution of observed price gaps. Deciles for the date are defined using residual revenue. Simulated model is described in text. Blue dots represent the simulated results from the model and the orange x represents the data.



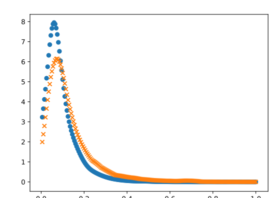
(e) 5th



(f) 6th

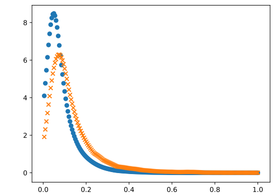


(g) 7th

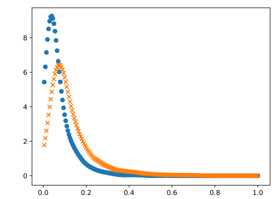


(h) 8th

Figure B.2: Distribution of price changes by decile of revenue (continued)



(i) 9th



(j) 10th

Figure B.2: Distribution of price changes by decile of revenue (continued)

Markets and Product Categories

We choose 32 markets on which we conduct our analysis. The designated market areas are defined by The Nielsen Company and correspond approximately (although not exactly) to a metropolitan statistical area (MSA). The full list is provided in Table B.3.

Table B.3: Designated Market Areas

DMA Name	
Portland-Auburn ME	Chicago IL
New York NY	St Louis MO
Philadelphia PA	Minneapolis-St Paul MN
Detroit MI	Kansas City MO-KS
Boston (Manchester) MA-NH	Oklahoma City OK
Ft Wayne IN	Nashville TN
Cleveland OH	Wichita-Hutchinson Plus KS
Washington DC (Hagerstown MD)	Des Moines-Ames IA
Baltimore MD	Little Rock-Pine Bluff AR
Cincinnati OH	Denver CO
Charleston SC	Phoenix AZ
Atlanta GA	Boise ID
Indianapolis IN	Albuquerque-Santa Fe NM
Louisville KY	Los Angeles CA
Hartford & New Haven CT	San Francisco-Oakland-San Jose CA
Tampa-St Petersburg (Sarasota) FL	Seattle-Tacoma WA

Table B.4: Product categories

Product Description	
Pie & Pastry Filling - Canned	Beer
Canned Fruit - Oranges	Near Beer/Malt Beverage
Canned Fruit - Peaches - Freestone	Gin
Gravy - Canned	Vodka
Seafood-Crab-Canned	Wine-Sangria
Seafood - Sardines - Canned	Wine-Sweet Dessert-Imported
Seafood-Tuna-Shelf Stable	Cleaners-Metal
Cat Food - Wet Type	Cleaners-Humidifiers/Vaporizers
Cat Food - Moist Type	Cooker Steamer And Dehydrator Appliance
Dog & Cat Treats	Air Purifier And Cleaner Appliance
Egg Mixes-Dry	Nutritional Supplements
Crackers - Sprayed Butter	Vitamins-B Complex W/C
Crackers - Oyster	Manicuring Needs
Coffee - Soluble	Hair Spray - Men's
Coffee Substitutes	Baby Care Products-Bath

In Table B.4 we provide the list of product categories used in our analysis. For measuring the relationship between the distribution of revenue and the local unemployment rate we increase our sample to include all product categories in the following (more broadly defined) product groups: Fruit - canned, Pet Food, Prepared Food-Ready-To-Serve, Coffee, Condiments Gravies and Sauces, Crackers, Household Cleaners, Beer, Wine, Liquor, Housewares- Appliances, Baby Needs, Hair Care, Vitamins.

Robustness

Table B.5: IRF : Coefficients

Periods	Quantile 1	Quantile 2	Quantile 3	Quantile 4	Quantile 5
1	-0.0202	-0.2955	-0.1320	-0.7483	-0.4627
	(0.1323)	(0.2079)	(0.1177)	(0.1612)	(0.3661)
2	0.0405	-0.3792	-0.2798	0.1718	0.4683
	(0.0876)	(0.1606)	(0.1593)	(0.1885)	(0.4243)
3	0.0620	0.0891	-0.0283	-0.1108	-1.1589
	(0.0875)	(0.1097)	(0.1372)	(0.1862)	(0.3980)
4	-0.0483	-0.0058	0.0996	-0.1068	0.0655
	(0.1663)	(0.2116)	(0.2611)	(0.4117)	(0.7516)
5	-0.1752	-0.3605	-0.5151	-0.7124	-0.7886
	(0.0609)	(0.2337)	(0.2355)	(0.2889)	(0.2000)
6	-0.0990	-0.0429	-0.0825	-0.2341	-0.1423
	(0.1409)	(0.1708)	(0.2891)	(0.2761)	(0.2723)
7	-0.0499	0.0653	0.0836	0.2636	0.1036
	(0.0859)	(0.1011)	(0.1066)	(0.1183)	(0.2906)
8	-0.1471	-0.2807	-0.3986	-0.4504	-0.9734
	(0.1123)	(0.1131)	(0.1420)	(0.1703)	(0.2622)
9	-0.3042	-0.4306	-0.6312	-0.6321	-0.5639
	(0.0901)	(0.1119)	(0.1410)	(0.1391)	(0.1595)
10	0.1740	0.3216	0.3538	0.4516	1.1247
	(0.1218)	(0.0754)	(0.1448)	(0.1994)	(0.3090)

Table B.5: IRF : Coefficients (continued)

Periods	Quantile 1	Quantile 2	Quantile 3	Quantile 4	Quantile 5
11	-0.3126	-0.2816	-0.0799	-0.0761	0.1426
	(0.0682)	(0.1211)	(0.2010)	(0.2776)	(0.3819)
12	0.0882	-0.1204	-0.6310	-0.8655	-1.9853
	(0.0641)	(0.0993)	(0.1290)	(0.1150)	(0.3187)
13	-0.1698	-0.4187	-0.3803	0.0952	0.5728
	(0.1123)	(0.1174)	(0.1953)	(0.2301)	(0.3264)
14	-0.1551	-0.1201	-0.2762	-0.3285	-0.3634
	(0.0802)	(0.1846)	(0.2508)	(0.3537)	(0.3614)
15	0.3777	0.4958	0.5292	0.2521	-0.3171
	(0.1374)	(0.1852)	(0.1668)	(0.1693)	(0.3139)
16	0.2552	0.3873	0.3010	0.3467	0.3793
	(0.0868)	(0.0994)	(0.1614)	(0.2276)	(0.6243)
17	-0.3776	-0.4809	-0.3095	-0.0649	0.2847
	(0.0887)	(0.1345)	(0.1589)	(0.2102)	(0.3227)
18	-0.0709	-0.2485	-0.1356	0.1220	-0.0350
	(0.0728)	(0.0956)	(0.0844)	(0.1095)	(0.1726)

Note: The dependent variable is the change in average change in log price within each quantile for each month. The quantiles are defined by market month. The coefficient reported is the appropriate lag of the monetary policy shocks from Paul (2018) except for 2008-2009 where we add the surprise announcements documented by Gorodnichenko Weber (2016). All standard errors are Newey-West with up to 12 lags.

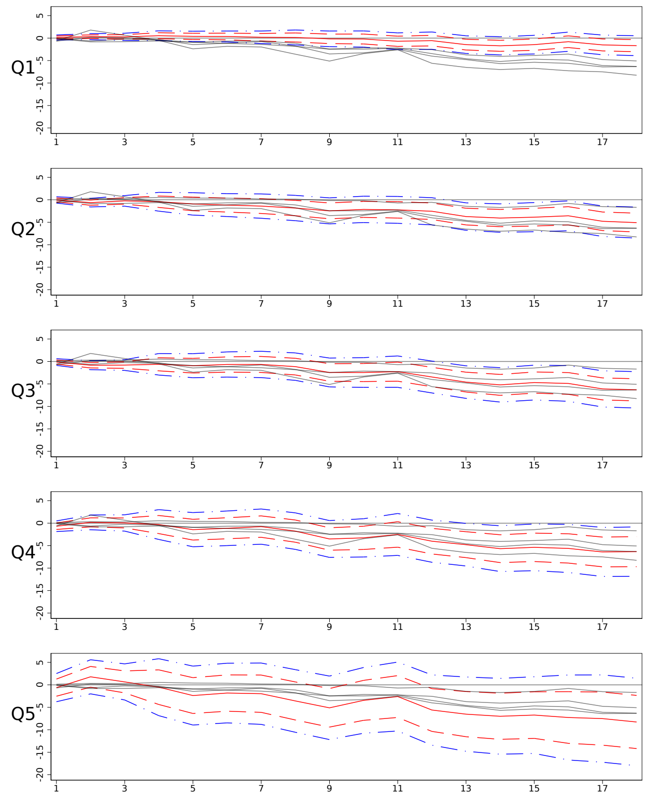


Figure B.3: Cumulative price response to a monetary shock by revenue quantile (excluding unscheduled meetings)

Note: This figure shows the cumulative impulse response of prices by revenue quantile, to an unexpected increase in the federal funds rate during a 30 minute window around FOMC announcements. Quantile 1 represents products with the lowest revenue and Quantile 5 represents those with the highest revenue. The dashed red lines represent one standard deviations confidence intervals. The dashed blue lines represent 90% confidence intervals.

Table B.6: IRF : Coefficients (excluding unscheduled meetings)

1	0.1492	-0.0281	-0.1278	-0.6805	-0.6177
	(0.3406)	(0.4239)	(0.4450)	(0.7159)	(1.9262)
2	0.1729	-0.6066	-0.7004	0.8610	2.4103
	(0.2040)	(0.3857)	(0.4306)	(0.6939)	(1.2548)
3	-0.0463	0.3950	0.0297	-0.1282	-1.1337
	(0.2845)	(0.3951)	(0.3680)	(0.4388)	(0.8108)
4	0.2593	-0.1938	0.1729	-0.3597	-1.1746
	(0.4517)	(1.0428)	(1.2558)	(1.6809)	(2.9283)
5	-0.1454	-0.4796	-0.3087	-1.1391	-1.8662
	(0.1942)	(0.8840)	(0.7911)	(1.2015)	(0.9781)
6	-0.0263	-0.2640	0.2659	0.3099	0.5587
	(0.2498)	(0.3059)	(0.4269)	(0.4520)	(0.6768)
7	-0.1747	-0.2213	0.0117	0.3723	-0.1466
	(0.4011)	(0.5390)	(0.5192)	(0.4384)	(0.9236)
8	-0.0429	-0.4348	-0.4856	-1.0034	-1.6106
	(0.5821)	(0.4280)	(0.5202)	(0.6158)	(0.9637)
9	-0.3108	-0.6335	-1.3043	-1.7526	-1.5293
	(0.3351)	(0.4471)	(0.5936)	(0.3037)	(0.7574)
10	-0.0349	0.3331	-0.0109	0.2513	1.6594
	(0.2966)	(0.2774)	(0.4761)	(0.6656)	(1.1321)

Table B.6: IRF : Coefficients (continued)

11	-0.5036	-0.1082	0.1960	0.7598	0.8543
	(0.3346)	(0.4020)	(0.6954)	(1.1036)	(1.4936)
12	0.1394	-0.3106	-1.1910	-1.4992	-3.0020
	(0.2397)	(0.3015)	(0.3594)	(0.4035)	(0.9655)
13	-0.8877	-1.1802	-1.1352	-0.7750	-0.9191
	(0.2098)	(0.2601)	(0.3892)	(0.4404)	(1.6616)
14	-0.2619	-0.3307	-0.6194	-0.8951	-0.4740
	(0.2762)	(0.4981)	(0.7075)	(0.9665)	(1.3010)
15	0.2633	0.1999	0.5185	0.3053	0.2661
	(0.3132)	(0.4335)	(0.4066)	(0.5322)	(0.7657)
16	0.6484	0.3009	-0.1964	-0.2436	-0.5395
	(0.2893)	(0.3398)	(0.5788)	(0.8998)	(2.3806)
17	-0.7116	-1.2152	-1.2177	-0.7907	-0.2388
	(0.3072)	(0.4478)	(0.4826)	(0.6034)	(1.2567)
18	-0.1728	-0.2994	-0.2026	0.0736	-0.7601
	(0.1740)	(0.3519)	(0.2174)	(0.4770)	(0.4244)

Note: Note: The dependent variable is the change in average change in log price within each quantile for each month. The quantiles are defined by market month. The coefficient reported is the appropriate lag of the monetary policy shocks from Paul (2018). All standard errors are Newey-West with up to 12 lags.

Table B.7: Revenue distribution over the business cycle: 30 product categories

	(1) Mean	(2) Median	(3) Std deviation	(4) Spread
unemployment	-0.921	-0.994	-0.332	-1.023
	(0.294)	(0.340)	(0.159)	(0.312)
Observations	141,121	141,121	140,482	141,121
R-squared	0.805	0.785	0.698	0.698

Note: This table includes data from 30 product categories used in the main analysis of this paper. The dependent variables are the moments of the log product revenue distribution across retailers for a given UPC-market-month. The independent variable of interest is the unemployment rate for a given market, computed from county level unemployment. All regressions include fixed effects for market, month, and product category. Standard errors clustered on market, month, and product category separately.

Average Frequency of Price Change over the Business Cycle

In this section we document the correlation between the average frequency of price change across all products with the business cycle. In Table B.8, we present regressions of the average frequency of price change computed using a revenue weighted average across the products in our main data. We regress these values on the national unemployment rate, the growth rate of Industrial Production, the cyclical component of HP-filtered Industrial production using ($\lambda = 129600$), and NBER recession dummies. As in Vavra (2014) and Bachmann et al. (2019) we find that the average frequency of price change is counter-cyclical in our sample.

In Table B.9 we present the same regressions except using a 6 month moving average of the frequency of price change on the left hand side. The relationship appears stronger with smoothed values, perhaps suggesting that the averaging removes noise. The Newey-West standard errors account for the extra auto-correlation that averaging may induce.

In Table B.10 we present correlations between the average frequency of price adjustment with the industrial production variables. Again, we find a negative correlation between average frequency of adjustment and the business cycle. Furthermore these results, which are directly comparable to those in Table 1 of Vavra (2014), are of similar magnitude as Vavra's values obtained from the broader CPI data. We therefore use the values in Tables B.8 and B.9 to calibrate the relationship between average frequency of adjustment and output in our quantitative model.

Table B.8: Regressions of average frequency of price change on business cycle measures

	(1)	(2)	(3)	(4)
Unemployment rate	0.113			
	(0.0888)			
IP cycle		-0.0346		
		(0.0337)		
IP growth			-0.210	
			(0.145)	
NBER dummy				1.267
				(0.383)
Observations	118	118	118	118
R-squared	0.010	0.00	0.01	0.049

Note: Dependent variable is the average frequency of price change weighted by the revenue of each product. Unemployment rate is the seasonally adjusted national unemployment rate from the Bureau of Labor Statistics. IP cycle is the cyclical component of industrial production from an HP filter. IP growth is the month on month growth rate of industrial production. NBER dummy are the recessions dates determined by the NBER. Standard errors are computed using Newey-West with a max lag of 12.

Table B.9: Regressions of average frequency of price change on business cycle measures (smoothed)

	(1)	(2)	(3)	(4)
Unemployment rate	0.210			
	(0.0980)			
IP cycle		-0.0678		
		(0.0367)		
IP growth			-0.324	
			(0.155)	
NBER dummy				1.444
				(0.315)
Observations	118	118	118	118
R-squared	0.130	0.055	0.053	0.238

Note: Dependent variable is the smoothed (ma-6) average frequency of price change weighted by the revenue of each product. Unemployment rate is the seasonally adjusted national unemployment rate from the Bureau of Labor Statistics. IP cycle is the cyclical component of industrial production from an HP filter. IP growth is the month on month growth rate of industrial production. NBER dummy are the recessions dates determined by the NBER. Standard errors are computed using Newey-West with a max lag of 12.

Table B.10: Correlation of Business Cycle with Avg. Freq.

	Average Frequency	Average Frequency (Smoothed)
IP Cycle	-0.0633	-0.2393
IP Growth	-0.0774	-0.2297

Note: We report simple correlation coefficients between average frequency of price adjustment and the business cycle. Frequency is computed as the revenue-weighed average frequency of adjustment across products. Smoothed is the moving average (ma-6) frequency of price adjustment. Unemployment rate is the seasonally adjusted national unemployment rate from the Bureau of Labor Statistics. IP cycle is the cyclical component of industrial production from an HP filter. IP growth is the month on month growth rate of industrial production.

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